Geliş/Received: 08.06.2026 | Revizyon/Revised: 28.08.2026 |Kabul/Accepted: 14.09.2026

KOCATEPEİİBFD

Research Article (Special Issue) | Araştırma Makalesi (Özel Sayı)

Assessing Sectoral Exposure to the Transformative Effects of Macrotrends Using Multi-Criteria Decision-Making Methods: Evidence from the Future of Jobs Report 2025

Ezgi Dilan Urmak Akçakaya Asst. Prof., Ardahan University, ezgidilanurmak@ardahan.edu.tr, 0000-0003-3472-1837

Gözde Koca Assoc. Prof., Bilecik Şeyh Edebali University, gozde.koca@bilecik.edu.tr, 0000-0001-6847-6812

Corresponding author/Sorumlu yazar: Ezgi Dilan Urmak Akçakaya

Abstract

This study aims to assess the intensity of sectoral exposure to the transformative effects of global macrotrends using Multi-Criteria Decision-Making (MCDM) methods. The analysis draws on data from the Future of Jobs Report 2025 and covers 22 sectors evaluated across 12 macrotrend criteria. Because the criterion values represent the extent to which each macrotrend is expected to affect sectoral transformation, all criteria were defined as maximization-oriented impact criteria. Accordingly, a higher value indicates greater transformation exposure rather than better sectoral performance. Criterion weights were determined using WENSLO, SPC, and equal weighting approaches, while sectoral rankings were obtained using PIV, CRADIS, and ARTASI. The rankings produced under the three weighting scenarios were integrated using the Borda method, and the consistency between the MCDM methods was examined through Spearman correlation analysis. The findings indicate that Mining and Metals has the highest overall transformation intensity, followed by Automotive and Aerospace and Supply Chain and Transportation. Conversely, Real Estate and Accommodation, Food, and Leisure exhibit the lowest relative levels of exposure to the macrotrends included in the analysis. The correlations between the rankings are positive, statistically significant, and very strong, with the highest agreement observed between PIV and CRADIS (ρ = 0.984). The study provides a multidimensional framework for identifying sectors facing the greatest cumulative transformation pressure and offers relevant insights for policymakers, sector representatives, and strategic decision-makers.

Keywords: MCDM, Sectoral Transformation, Future of Jobs, Macrotrends **JEL Codes:** C02, C44, J21, O33

Makrotrendlerin Dönüştürücü Etkilerine Sektörel Maruziyetin Çok Kriterli Karar Verme Yöntemleriyle Değerlendirilmesi: Future of Jobs Report 2025 Temelli Bir İnceleme

Öz

Bu çalışma, küresel makrotrendlerin dönüştürücü etkilerine yönelik sektörel maruziyet yoğunluğunu Çok Kriterli Karar Verme (ÇKKV) yöntemleriyle değerlendirmeyi amaçlamaktadır. Analizde Future of Jobs Report 2025'ten elde edilen veriler kullanılmış ve 12 makrotrend kriteri kapsamında 22 sektör incelenmiştir. Kriter değerleri, her bir makrotrendin sektörel dönüşümü etkileme düzeyini gösterdiğinden, tüm kriterler maksimizasyon yönlü etki kriterleri olarak tanımlanmıştır. Buna göre yüksek bir değer, daha iyi sektörel performansı değil, daha yüksek dönüşüm maruziyetini ifade etmektedir. Kriter ağırlıkları WENSLO, SPC ve eşit ağırlıklandırma yaklaşımlarıyla belirlenmiş; sektör sıralamaları ise PIV, CRADIS ve ARTASI yöntemleri kullanılarak elde edilmiştir. Üç ağırlıklandırma senaryosu altında oluşturulan sıralamalar Borda yöntemiyle bütünleştirilmiş, ÇKKV yöntemleri arasındaki sıralama tutarlılığı ise Spearman korelasyon analiziyle incelenmiştir. Bulgular, Mining and Metals sektörünün en yüksek toplam dönüşüm yoğunluğuna sahip olduğunu; bu sektörü Automotive and Aerospace ile Supply Chain and Transportation sektörlerinin izlediğini göstermektedir. Buna karşılık Real Estate ile Accommodation, Food, and Leisure sektörleri, analize dâhil edilen makrotrendlere görece en düşük maruziyet düzeylerini sergilemiştir. Yöntemler arasındaki korelasyonların pozitif, istatistiksel olarak anlamlı ve oldukça güçlü olduğu, en yüksek uyumun PIV ile CRADIS arasında gerçekleştiği belirlenmiştir (ρ = 0,984). Çalışma, en yüksek toplam dönüşüm baskısıyla karşı karşıya olan sektörlerin belirlenmesine yönelik çok boyutlu bir çerçeve sunmakta; politika yapıcılar, sektör temsilcileri ve stratejik karar alıcılar açısından önemli çıkarımlar sağlamaktadır.

Anahtar Kelimeler: ÇKKV, Sektörel Dönüşüm, Geleceğin İşleri, Makrotrendler **JEL Kodları:** C02, C44, J21, O33

Introduction

Industry 4.0, digital transformation, and smart technologies have recently had a large-scale impact on the international economy, employment, and workforce. Artificial intelligence, robotics, automation, and other technological advancements are causing significant transformations in almost all sectors. These transformations, particularly in business, production, and competition

How to cite this article / Bu makaleye atıf vermek için:
Urmak Akçakaya, E. D., & Koca, G., (2026). Assessing Sectoral Exposure to the Transformative Effects of Macrotrends Using Multi-Criteria Decision-Making Methods: Evidence from the Future of Jobs Report 2025. *KOCATEPEİİBFD, 28*(Special Issue), 153-168. https://doi.org/10.33707/akuiibfd.1966395

processes, have attracted the attention of many researchers. For example, Brynjolfsson and McAfee (2014) stated that technological progress not only shapes sectoral production processes but also increases the structure, efficiency, productivity, and competitiveness of the workforce. Indeed, with the widespread adoption of digital technologies and increased automation, structural changes are manifesting themselves, and the future of the labor market is being reshaped. On the other hand, energy transition, along with sustainability policies, is among the leading dynamics shaping the future at the sectoral level. With the increasing impact of climate change, carbon reduction, green transition, and renewable energy policies and investments are seen to be increasing day by day. These developments in environmental sustainability policies are affecting sectors such as energy, transportation, manufacturing, and infrastructure. Geels (2018) underlines that the energy and infrastructure sectors are the sectors experiencing the most intense sustainability transitions. *The World Energy Outlook Report* discusses the impact of the transformation of world economies into low-carbon economies on global sectoral structures (International Energy Agency, 2024).

Sectoral structural transformations also emerge under the influence of other trends. For example, global trade restrictions, slowing economic growth, demographic changes, and geopolitical divisions can be counted among these trends. Chaotic processes such as disruptions in supply chains, regional conflicts, economic uncertainties, and energy crises following the COVID-19 pandemic have once again highlighted the importance of sectoral resilience. Thus, government incentives, industrial policies, and public investments have become the determining dynamics of sectoral transformation. As Mazzucato (2018) also points out, public interventions are quite important in economic transformations. Because public interventions, in addition to their regulatory function, also assume an innovative and guiding role in these processes.

The 2025 Future of Work Report, published by the World Economic Forum, is one of the most comprehensive studies assessing global transformation processes and the future. This report examines in detail the impact of numerous macro trends across various sectors. Examples of these macro trends include expanded access, climate change adaptation investments, government incentives, geopolitical risks, global trade restrictions, and demographic shifts (World Economic Forum, 2025).

Evaluating the effects of global macrotrends on sectors constitutes a complex and multidimensional assessment problem because sectoral transformation is simultaneously shaped by technological, economic, environmental, demographic, social, and geopolitical forces. Multi-Criteria Decision-Making (MCDM) methods provide a systematic framework for examining these effects collectively and comparing sectors across multiple dimensions. In the present study, MCDM is not used to determine whether one sector performs better than another. Instead, it is used to assess the cumulative intensity of sectoral exposure to macrotrend-driven transformation and to construct comparative rankings based on this exposure.

Most studies drawing on the Future of Jobs Report focus on workforce transformation, automation, digital skills, artificial intelligence, and changing occupational structures. For example, Frey and Osborne (2017) argue that automation will reshape the structure of employment and expose certain occupational groups to a greater risk of technological substitution. Similarly, Di Nardo et al. (2022) examine how digitalization and reskilling processes influence labor markets and the future structure of work. However, studies that comparatively assess the extent to which multiple global macrotrends collectively affect different sectors remain limited. In particular, the existing literature lacks an integrated MCDM framework that treats the reported percentages as indicators of transformation exposure and evaluates technological, economic, environmental, demographic, social, and geopolitical pressures in a common direction.

Accordingly, this study aims to assess the intensity of sectoral exposure to the transformative effects of global macrotrends using MCDM methods. Based on data from the Future of Jobs Report 2025, 22 sectors are evaluated across 12 macrotrend criteria. Because each criterion value represents the percentage of organizations within a sector expecting the relevant macrotrend to drive business transformation, a higher value indicates a greater level of transformative impact. Therefore, all 12 criteria are defined as maximization-oriented impact criteria. In this framework, maximization does not imply that a macrotrend is beneficial or desirable; it means only that a higher percentage represents greater sectoral exposure to transformation. Criterion weights are determined using WENSLO, SPC, and equal weighting approaches, while sectoral rankings are obtained using PIV, CRADIS, and ARTASI. The Borda method is employed to integrate the rankings, and Spearman correlation analysis is used to examine the consistency between the MCDM methods.

This study contributes to the literature in both conceptual and methodological terms. Conceptually, it distinguishes transformation intensity from conventional notions of sectoral performance, success, or desirability. Thus, sectors receiving higher scores are interpreted as being more strongly affected by the combined transformative pressures of macrotrends, rather than as being more successful or better performing. Methodologically, the study combines objective and equal weighting approaches with three MCDM ranking methods and the Borda aggregation procedure, thereby providing a robustness-oriented evaluation of sectoral transformation exposure. The findings are expected to assist policymakers, sector representatives, investors, and strategic decision-makers in identifying the sectors facing the greatest cumulative transformation pressure and in developing appropriate adaptation, workforce, investment, and resilience strategies.

The study consists of five chapters. Following the introduction, the first chapter reviews the literature. The second chapter describes the dataset and methods used in the research. The third chapter presents the findings of the research. The fourth chapter discusses the findings obtained from the analyses. The final chapter addresses the research results, the limitations of the study, and suggestions for future research.

1. Literature Review

Table 1 presents a literature review of the WENSLO, SPC, PIV, CRADIS, and ARTASI methods used in this study. Table 1 shows that although these methods are new, they are used in different application areas.

Table 1. Literature Review

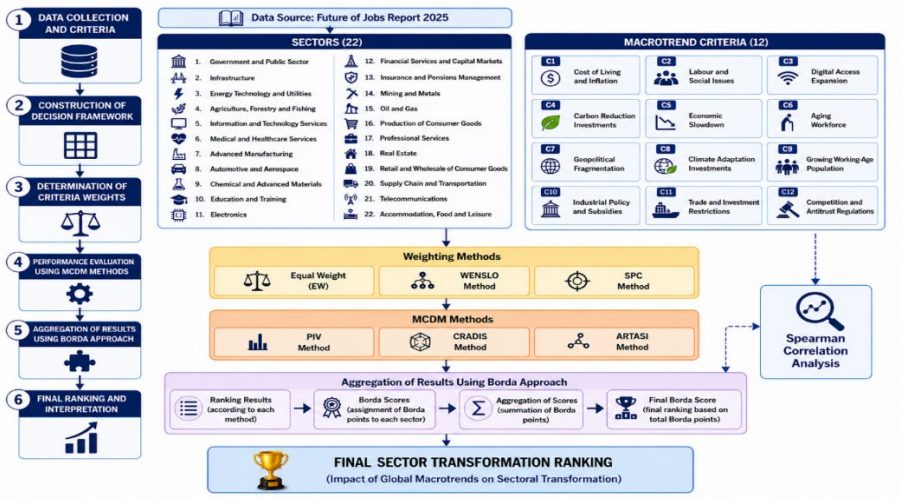
Studies on the WENSLO Method		
Kara et al., 2024	Evaluating sustainable brand value performance.	The most important factor in the evaluation was the green product leadership criterion.
Yarlıkaş, 2025	Assessment of the knowledge-based development levels of Northern European countries.	In evaluating the information performance levels of Northern European countries, the most important criterion was determined to be Research, Development and Innovation, while the least important criterion was Information and Communication Technology.
Keleş and Kahveci, 2025	Evaluation of the logistics performance of European Union candidate and member countries.	Infrastructure and customs criteria were identified as the most important criteria, while timeliness was deemed the least important.
Subramanian et al., 2025	Supplier selection	The subcontractor's quality performance has been identified as the most important criterion.
Kara et al., 2025	Choosing a sustainable brand logo.	Evoking positive emotions and building relationships with consumers has been identified as the most important criterion.
Wang et al., 2026	Determining strategic warehouse locations.	Proximity to suppliers has been identified as the most important criterion.
Studies on the SPC Method		
Taşçı, 2025	Optimal portfolio selection	Return on equity, return on assets, and growth-oriented financial indicators have been identified as important criteria in investment decisions.
Kahreman, 2026	Evaluation of production capacity performance.	Transportation has been identified as the most important criterion.
Ali, 2026	Evaluation of advanced filtration techniques.	Membrane filtration, activated carbon filtration, advanced oxidation processes, artificial wetlands, and ultraviolet disinfection were identified as key criteria.
Studies on the PIV Method		
Khan et al., 2019	Choosing an e-learning website	Tutorialspoint website was chosen as the best alternative.
Ersoy, 2021	Application of the PIV method with negative data.	In cases where the decision matrix contains negative values, the min-max normalization technique has been chosen as the most suitable technique for using the PIV method.
Trung et al., 2022	Evaluation of turning processes	The RAFSI and PIV methods were compared. similar rankings were obtained with both methods.
Erdoğan, 2022	Evaluating the financial performance of banks	Garanti Bank ranked first, while ICBC Turkey Bank ranked last.
Nguyen, 2024	Selection of crankshaft manufacturing material	S48C has been identified as the best alternative.
Van Dua et al., 2024	Selection of manufacturing materials	MARA was determined to be the most suitable method for selecting lubricants for two-stroke engines, while RAM was determined to be the most suitable method for selecting materials for screw shafts and gears.
Dudić, 2024	Selection of plastic injection molding machines.	The JSW J550E-C5 has been selected as the best machine.
Keleş and Alaca, 2023	Evaluation of digital marketing technologies.	Artificial intelligence ranked first, while big data came in last.
Durdu et al., 2025	Evaluation of the financial performance of insurance companies.	The most successful company was determined to be Türkiye Sigorta.

Studies on the CRADIS Method		
Puška et al., 2023	An assessment of the knowledge economies of European Union countries.	In the study, Sweden, Finland, and Denmark ranked in the top three.
Puška et al., 2023	Evaluation of Balkan countries according to the economic freedom index.	The study identified Bulgaria as the best country in terms of economic freedom, while Montenegro was the worst.
Keleş, 2023	An assessment of livable powerhouse cities in G7 countries and Turkey.	The study ranked Tokyo and New York in the top positions, while Istanbul came in last.
Stojanović, 2024	Selection of a construction contractor for the construction of a solar power plant.	In the study, contractor C6 came in first place.
Kahreman, 2024	Evaluation of Turkey's sustainable development and sub-dimension performance.	The study determined that 2011 was the best year in terms of sustainable development and economic performance.
Şahin and Özdemir 2025	Evaluation of the macroeconomic performance of G8 countries.	The evaluation resulted in Germany ranking first and Italy ranking last.
Azgun and Akyurt, 2026	Evaluation of the performance of nature parks.	The best nature park in terms of ecotourism has been determined as Koç Kayası Nature Park. Hızırilyas Hill Nature Park was determined as the nature park with the lowest performance.
Studies on the ARTASI Method		
Aydın Ünal, 2025	Evaluation of the university's sustainability performance.	Istanbul Technical University ranked first, while Selçuk University ranked thirtieth.
Taşcı, 2025	Optimal portfolio selection	Doğuş Otomotiv, Ford Otosan, and Türk Traktör were among the top-ranked companies.
Keleş and Kahveci, 2025	Evaluation of the logistics performance of European Union candidate and member countries.	Finlandia ranked first in the evaluation, while Cyprus came in last.
Pamucar et al., 2025	Evaluating the efficiency of airports worldwide.	Chubu Centrair ranks first among 5-star airports.
Chen, 2025	Evaluating the clothing designs of ethnic minorities.	Alternative A3 came in first place, while alternative A9 came in last place.
Chen and Zhang, 2025	Evaluation of the eco-efficiency of petrochemical companies.	Alternative A1 came in first place, while alternative A2 came in last place.

2. Data and Methods

The Data and Methods section is divided into two subsections. The first section, "Data," presents information on the criteria and sectors used in the study, while the second section summarizes the Multi-Criteria Decision Making (MCDM) methods used in the analysis process (Equal weighting, WENSLO, SPC, PIV, CRADIS, and ARTASI).

Fig. 1. Flow Chart



Source: This figure was created using an artificial intelligence tool.

2.1. Data

This study uses 12 macrotrend criteria to assess the intensity of sectoral exposure to global transformation pressures. The data were obtained from the sector-specific findings reported in the *Future of Jobs Report 2025* published by the World Economic Forum. The criterion values are expressed as percentages and indicate the extent to which organizations operating in each sector expect the relevant macrotrend to drive business transformation. Therefore, these values do not indicate whether the effects of a macrotrend are positive or negative; rather, they represent the magnitude of its expected transformative impact on the relevant sector. A total of 22 sectors were included in the analysis: "Accommodation, Food, and Leisure", "Advanced Manufacturing", "Agriculture, Forestry and Fishing", "Automotive and Aerospace", "Chemical and Advanced Materials", "Education and Training", "Electronics", "Energy Technology and Utilities", "Financial Services and Capital Markets", "Government and Public Sector", "Information and Technology Services", "Infrastructure", "Insurance and Pensions Management", "Medical and Healthcare Services", "Mining and Metals", "Oil and Gas", "Production of Consumer Goods", "Professional Services", "Real Estate", "Retail and Wholesale of Consumer Goods", "Supply Chain and Transportation", and "Telecommunications". Information on the definitions, explanations, units, and impact directions of the macrotrend criteria used in the study is presented in Table 2.

Table 2. Information on Macrotrend Criteria Used in the Study

Criterion	Definition	Explanation / Relationship	Unit	Direction
C1	Rising cost of living and inflation	The extent to which inflation and rising living costs affect sector transformation.	%	Benefit
C2	Increased focus on labor and social issues.	The impact of labor rights, equality, and social issues on sector transformation.	%	Benefit
C3	Expansion of digital access	The extent to which increased digital infrastructure and access accelerate sector transformation.	%	Benefit
C4	Efforts and investments to reduce carbon emissions.	The impact of carbon reduction policies and investments on sector transformation.	%	Benefit
C5	Slowing economic growth	The extent to which economic recession creates transformative pressure on sectors	%	Benefit
C6	Aging and declining working-age population	The impact of demographic contraction on sectoral transformation.	%	Benefit
C7	Increased geopolitical divisions and conflicts	The impact of global political tensions on sectors	%	Benefit
C8	Climate change adaptation efforts and investments	The impact of climate adaptation strategies and investments on sector transformation.	%	Benefit
C9	Increase in the working-age population	Opportunities that demographic growth presents to sectors	%	Benefit
C10	Increased government subsidies and industrial policies	The impact of government support and industrial policies on sector transformation.	%	Benefit
C11	Increased global trade and investment restrictions.	The impact of trade barriers on sectoral transformation.	%	Benefit
C12	Stricter competition and antitrust regulations.	The impact of competition regulations on industry transformation.	%	Benefit

Source: World Economic Forum, Future of Jobs Report 2025.

As shown in Table 2, all 12 criteria were defined as maximization-oriented impact criteria. This common directional specification was adopted because higher percentages indicate that a larger proportion of organizations operating in the relevant sector expect the macrotrend to drive business transformation. In this context, "Max" does not imply that the macrotrend is beneficial, desirable, or associated with better sectoral performance. It indicates only that a higher criterion value represents a greater level of sectoral exposure to the relevant transformative force.

For example, an 80% value for rising cost of living and inflation (C1) represents greater inflation-related transformation pressure than a value of 30%. Similarly, a 70% value for geopolitical divisions and conflicts (C7) indicates greater geopolitical transformation exposure than a value of 25%. The same interpretation applies to the expansion of digital access (C3): a higher percentage represents a stronger digital transformation effect on the sector. Accordingly, all criteria were evaluated in the same direction:

$C1, C2, \ldots, C12 \rightarrow Max$

Consequently, no cost-specific inversion or normalization procedure was applied to any criterion in the PIV, CRADIS, or ARTASI analyses. Higher final scores were interpreted as indicating greater cumulative exposure to macrotrend-driven transformation rather than superior sectoral performance or a more desirable sectoral position.

2.2. Method

In this study, sectors were evaluated using multi-criteria decision-making methods. First, criterion weights were calculated using WENSLO, SPC, and equal weighting methods. Then, PIV, CRADIS, and ARTASI methods were used to obtain sector rankings. Since the criterion values represent the extent of the transformative impact of macrotrends, all 12 criteria were treated as maximization-oriented impact criteria. Accordingly, the normalization procedures for maximization criteria were applied uniformly, and no cost-oriented inversion was performed. Higher scores and rankings were interpreted as indicating greater sectoral exposure to macrotrend-driven transformation rather than better sectoral performance. The steps of the methods are presented in Appendix 1.

WENSLO is a weighting method proposed by Pamucar et al. in 2023. In this method, criterion weights are determined based on the ratio between the envelope value and the slope value of each criterion. When the envelope value is high and the slope value is low, the criterion weight is higher (Pamucar et al., 2023). The method is based on statistical concepts. The criterion class range is obtained using Sturges' rule. The use of Sturges' rule prevents overfitting or oversmoothing, ensuring the determination of the optimal number of divisions or intervals (Biswas et al., 2025). The biggest advantage of the WENSLO method is that the criterion weights are obtained independently of individual judgment or expert group. Another advantage of the WENSLO method is that criterion orientation does not affect the calculation of criterion weights. The independence of the input-data normalization procedure from criterion orientation makes the method more reliable and stable (Pamucar et al., 2023).

The SPC (Symmetry Point of Criterion) method was introduced to the literature by Gligorić et al. in 2023. Used in determining objective criterion weights, the SPC method measures the effect of a criterion on its weights by using its point of symmetry, i.e., the modulus of symmetry. A higher modulus value indicates a higher degree of importance (Chatterjee and Chakraborty, 2024). Considering the dominant role of criterion importance levels on the final ranking in MCDM processes, the method's independence from subjective judgments allows decision-makers to obtain more consistent, reliable, and unbiased results. Another important advantage of the method is its ability to distribute weighting coefficients homogeneously and evenly. Thanks to its flexible and understandable structure, the SPC method can be easily integrated with traditional MCDM techniques and successfully applied to solving complex problems in different disciplines (Gligorić et al., 2023).

The PIV method was developed by Mufazzal and Muzakkir in 2018. This method is based on the positive ideal solution principle, according to which an alternative positioned closer to the ideal solution receives a higher ranking (Goswami et al., 2022). The method evaluates the proximity of alternatives to the ideal value using the Proximity Index. The Proximity Index represents the linear difference between the normalized value of each alternative and the corresponding ideal value. In this method, the ranking is based on the absolute distribution, which considers only the positive ideal solution, rather than the relative distribution used in TOPSIS, which considers both positive and negative ideal solutions. The PIV method offers a significant advantage in preventing or minimizing the rank-reversal problem and provides a reliable framework for various multi-criteria decision-making problems (Mufazzal and Muzakkir, 2018).

Developed by Puška et al. in 2021, CRADIS is a method designed to determine the deviation of alternatives from the ideal and anti-ideal solutions. CRADIS was developed by creating a new method using the procedures of existing methods. This method is a combination of steps from ARAS (Supplemental Ratio Assessment), MARCOS (Measurement and Ranking of Alternatives by Compromise Solution), and TOPSIS methods. CRADIS aims to minimize the disadvantages of these methods while leveraging their advantages (Puška et al., 2022). Multi-criteria methods based on utility value, such as ARAS, MARCOS, and TOPSIS, offer decision-makers several advantages, including ease of computation, comprehensibility, and reliability of results. CRADIS, on the other hand, has a simpler, more practical, functional, and effective algorithm for evaluating and prioritizing existing alternatives (Krishankumar and Ecer, 2023).

The ARTASI method was developed by Pamucar et al. in 2024 for the purpose of evaluating alternatives. In this method, the normalization/standardization interval of the elements of the initial decision matrix can be adjusted. Eliminating the problem of reverse ranking, the method has the ability to adapt to dynamic environments and possesses a high degree of generalization (Pamucar et al., 2024). Using a ratio-based approach, the ARTASI method creates distinctive and consistent rankings by evaluating the relative distances of alternatives to ideal and anti-ideal solutions (Aydın Ünal, 2025).

3. Findings

This study aims to determine the intensity of sectoral exposure to the transformative effects of global macrotrends. For this purpose, the extent to which sectors are affected by macrotrends was analyzed using different criterion-weighting and Multi-Criteria Decision-Making (MCDM) methods. In this section, the criterion weights are first evaluated, followed by a comparison of the sectoral transformation-exposure rankings obtained using PIV, CRADIS, and ARTASI. Finally, the consistency between the rankings produced by these methods is examined through Spearman correlation analysis. In this study, criterion weights were first

calculated using the WENSLO, SPC, and equal weighting methods. The resulting criterion weights are presented in Table 3.

Table 3. Criterion Weights

Criterion	WENSLO	SPC	EQUAL	Criterion	WENSLO	SPC	EQUAL
C1	0,04151706	0,00029033	0,08333333	C7	0,00029033	0,00026696	0,08333333
C2	0,03971830	0,00029809	0,08333333	C8	0,00029809	0,00047675	0,08333333
C3	0,05150552	0,00029327	0,08333333	C9	0,00029327	0,00030097	0,08333333
C4	0,08048286	0,00048068	0,08333333	C10	0,00048068	0,53828566	0,08333333
C5	0,05198304	0,00027894	0,08333333	C11	0,00027894	0,00078552	0,08333333
C6	0,05609640	0,00032577	0,08333333	C12	0,00032577	0,45791705	0,08333333

Table 3 shows that in the WENSLO method, the criteria with the highest weights are C11, C12, and C10, respectively. Decision-makers should give due importance to these high-weight criteria. In the SPC method, it was determined that criteria C10 and C12 have significantly higher weight values compared to other criteria. In the equal weighting approach, all criteria were evaluated with the same weight value. After determining the criterion weights, sectoral transformation-exposure levels were first analyzed using the PIV method. The PIV ranking results are presented in Table 4.

Table 4. PIV Method Results

Sectors	Wenslo	SPC	Equal	Borda Points	Sectors	Wenslo	SPC	Equal	Borda Points
Mining and Metals	1	1	2	65	Production of Consumer Goods	13	18	8	30
Automotive and Aerospace	2	2	1	64	Oil and Gas	15	9	19	26
Supply Chain and Transportation	3	3	3	60	Insurance and Pensions Management	16	20	4	26
Advanced Manufacturing	5	5	5	54	Electronics	10	15	13	25
Agriculture, Forestry and Fishing	6	4	7	52	Retail and Wholesale of Consumer Goods	14	16	11	25
Chemical and Advanced Materials	4	11	6	48	Telecommunications	18	13	18	23
Financial Services and Capital Markets	7	12	9	41	Government and Public Sector	17	19	15	18
Information and Technology Services	11	6	14	38	Education and Training	20	14	20	15
Infrastructure	9	8	12	37	Professional Services	19	17	17	16
Medical and Healthcare Services	12	7	10	37	Accommodation, Food, and Leisure	21	21	21	6
Energy Technology and Utilities	8	10	16	35	Real Estate	22	22	22	3

Table 4 shows that Mining and Metals ranks first in the PIV results, with 65 Borda points. It is followed by Automotive and Aerospace with 64 points and Supply Chain and Transportation with 60 points. These results indicate that the three sectors have the highest cumulative exposure to the transformative effects of the macrotrends included in the analysis. Conversely, Real Estate ranks last, indicating the lowest relative transformation intensity under the PIV method. Sectoral transformation-exposure levels were subsequently evaluated using the CRADIS method, and the results are presented in Table 5.

Table 5. CRADIS Method Results

Sectors	Wenslo	SPC	Equal	Borda Points	Sectors	Wenslo	SPC	Equal	Borda Points
Mining and Metals	1	1	2	65	Production of Consumer Goods	12	18	8	31
Automotive and Aerospace	2	2	1	64	Insurance and Pensions Management	14	20	4	31
Supply Chain and Transportation	3	3	3	60	Electronics	13	15	13	28
Advanced Manufacturing	5	6	5	53	Retail and Wholesale of Consumer Goods	15	16	11	27
Agriculture, Forestry and Fishing	6	4	7	52	Oil and Gas	16	10	20	23
Chemical and	4	11	6	48	Telecommunications	17	13	17	22

Advanced Materials									
Medical and Healthcare Services	9	7	10	43	Government and Public Sector	18	19	15	17
Financial Services and Capital Markets	7	12	9	41	Education and Training	20	14	19	16
Infrastructure	8	8	12	41	Professional Services	19	17	18	15
Information and Technology Services	11	5	14	39	Accommodation, Food, and Leisure	21	21	21	6
Energy Technology and Utilities	10	9	16	34	Real Estate	22	22	22	3

According to Table 5, Mining and Metals ranks first in the CRADIS results, followed by Automotive and Aerospace and Supply Chain and Transportation. Advanced Manufacturing, Agriculture, Forestry and Fishing, and Chemical and Advanced Materials also occupy relatively high positions. These rankings indicate that the sectors are exposed more intensively to the combined transformative effects of the macrotrends. In contrast, Real Estate and Accommodation, Food, and Leisure are positioned at the bottom of the ranking, indicating comparatively lower transformation exposure. The ARTASI results are presented in Table 6.

Table 6. Results of the ARTASI Method

Sectors	**Wenslo**	**SPC**	**Equal**	**Borda Points**	**Sectors**	**Wenslo**	**SPC**	**Equal**	**Borda Points**
Mining and Metals	1	1	2	65	Production of Consumer Goods	12	18	8	31
Automotive and Aerospace	2	2	1	64	Insurance and Pensions Management	14	20	4	31
Supply Chain and Transportation	3	3	3	60	Electronics	13	15	13	28
Advanced Manufacturing	5	6	5	53	Retail and Wholesale of Consumer Goods	15	16	11	27
Agriculture, Forestry and Fishing	6	4	7	52	Oil and Gas	16	10	20	23
Chemical and Advanced Materials	4	11	6	48	Telecommunications	17	13	17	22
Medical and Healthcare Services	9	7	10	43	Government and Public Sector	18	19	15	17
Financial Services and Capital Markets	7	12	9	41	Education and Training	20	14	19	16
Infrastructure	8	8	12	41	Professional Services	19	17	18	15
Information and Technology Services	11	5	14	39	Accommodation, Food, and Leisure	21	21	21	6
Energy Technology and Utilities	10	9	16	34	Real Estate	22	22	22	3

Table 6 shows that Mining and Metals also ranks first according to the ARTASI method. Automotive and Aerospace and Supply Chain and Transportation occupy the second and third positions, respectively. Advanced Manufacturing, Agriculture, Forestry and Fishing, and Chemical and Advanced Materials also display relatively high levels of transformation exposure. Conversely, Real Estate ranks last, while Accommodation, Food, and Leisure occupies the second-lowest position. These findings indicate that the sectors at the top of the ranking face greater cumulative transformation pressure rather than demonstrating better sectoral performance. The overall rankings of the three methods were evaluated together, and the resulting integrated rankings are presented in Table 7.

Table 7. Overall Ranking Results of the Methods

Sectors	**PIV**	**CRADIS**	**ARTASI**	**Sectors**	**PIV**	**CRADIS**	**ARTASI**
Mining and Metals	1	1	1	Energy Technology and Utilities	11	11	13
Automotive and Aerospace	2	2	2	Insurance and Pensions Management	14	13	14
Supply Chain and Transportation	3	3	3	Retail and Wholesale of Consumer Goods	16	15	12
Advanced Manufacturing	4	4	4	Electronics	15	14	15
Agriculture, Forestry and Fishing	5	5	5	Oil and Gas	13	16	18
Chemical and Advanced Materials	6	6	6	Telecommunications	17	17	17
Infrastructure	9	9	7	Government and Public Sector	18	18	19

Medical and Healthcare Services	10	7	8	Professional Services	19	20	16
Financial Services and Capital Markets	7	8	11	Education and Training	20	19	20
Information and Technology Services	8	10	9	Accommodation, Food, and Leisure	21	21	21
Production of Consumer Goods	12	12	10	Real Estate	22	22	22

Table 7 shows a high degree of consistency among the PIV, CRADIS, and ARTASI rankings. Mining and Metals ranks first in all three methods, followed by Automotive and Aerospace and Supply Chain and Transportation. Similarly, Advanced Manufacturing, Agriculture, Forestry and Fishing, and Chemical and Advanced Materials occupy the same positions across the three rankings. These results demonstrate that the sectors at the top of the rankings are consistently identified as those facing the greatest cumulative transformation pressure. At the lower end, Accommodation, Food, and Leisure and Real Estate rank 21st and 22nd, respectively, in all three methods, indicating comparatively limited exposure to the combined effects of the macrotrends included in the analysis. Some differences are observed among the middle-ranking sectors, reflecting the distinct mathematical structures of the methods. To determine the relationship between the methods, Spearman correlation analysis was performed, and the results are presented in Table 8.

Table 8. Spearman Correlation Results Between Methods

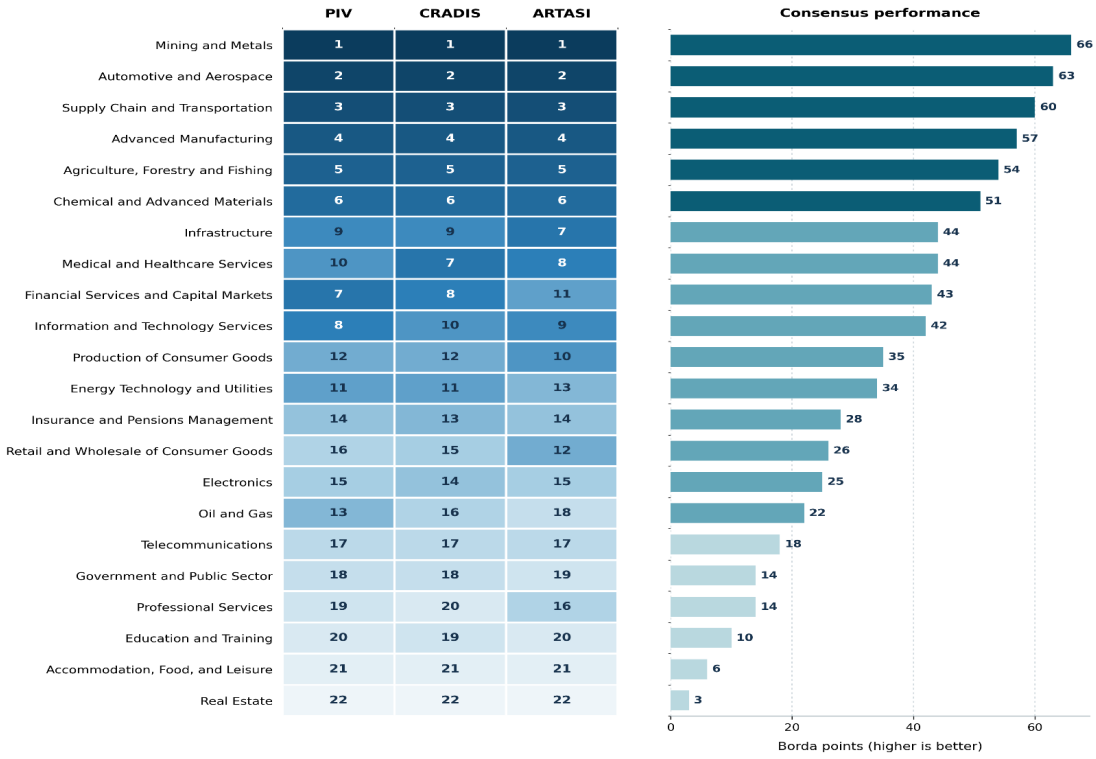
Methods	Spearman Correlation	p value
PIV – CRADIS	0.984	<0.001
PIV – ARTASI	0.953	<0.001
CRADIS – ARTASI	0.968	<0.001

The highest correlation was observed between the PIV and CRADIS rankings ($\rho = 0.984$; $p < 0.001$). Strong positive correlations were also found between CRADIS and ARTASI ($\rho = 0.968$; $p < 0.001$) and between PIV and ARTASI ($\rho = 0.953$; $p < 0.001$). These findings indicate that the sectoral transformation-exposure rankings produced by the three MCDM methods are highly consistent. The statistically significant and very strong correlations also demonstrate that the main findings are robust to the mathematical differences among the ranking methods.

4. Discussion

This study aims to examine and evaluate the transformative effects of global macrotrends at the sectoral level. For this purpose, multi-criteria decision-making (MCDM) methods are used, and a comprehensive analysis is conducted. The findings of the study show that the infrastructure, energy, and agriculture sectors, as well as Public Administration, are most affected by global transformation processes (Figure 2). The insurance and pension management sector, however, showed a low performance, indicating that this sector is relatively less affected by macrotrends.

Fig. 2. Findings



The findings are broadly consistent with the transformation processes identified in the *Future of Jobs Report 2025*. The report emphasizes that technological change, the green transition, economic uncertainty, demographic shifts, government policies, geopolitical tensions, and trade restrictions simultaneously reshape industries (World Economic Forum, 2025). In the present study, Mining and Metals, Automotive and Aerospace, and Supply Chain and Transportation occupy the highest positions across the PIV, CRADIS, and ARTASI rankings. This result indicates that sectors closely connected to strategic raw materials, global production networks, international trade, technological change, and decarbonization pressures face particularly intensive transformation.

Mining and Metals ranks first according to all three MCDM methods. This result indicates that the sector is simultaneously exposed to economic, technological, environmental, geopolitical, and regulatory transformation pressures. Strategic raw-material demand, energy-intensive production, carbon-reduction policies, international trade restrictions, and geopolitical divisions can collectively explain the sector's high transformation intensity. The growing importance of the energy transition and decarbonization is consistent with Sovacool et al. (2020), who emphasize the extensive economic and technological effects of energy transitions. Similarly, Geels (2018) argues that sustainability transitions create broad structural changes across production, transportation, infrastructure, and energy systems. The *World Energy Outlook* also indicates that the energy transition will have important consequences for sectoral structures and future workforce requirements (IEA, 2024). Therefore, the first-place ranking of Mining and Metals should not be interpreted as superior sectoral performance but as the highest cumulative exposure to macrotrend-driven transformation.

Automotive and Aerospace and Supply Chain and Transportation rank second and third, respectively, across all methods. The high transformation exposure of Automotive and Aerospace can be associated with digitalization, automation, carbon-emission reduction, changing trade regulations, geopolitical uncertainty, and the restructuring of global production networks. Similarly, Supply Chain and Transportation is directly affected by trade and investment restrictions, geopolitical conflicts, energy-transition requirements, digital access, and changing regulatory conditions. Brynjolfsson and McAfee (2014) emphasize that digitalization produces critical changes in production processes, service activities, and organizational structures. Technological transformation and digital infrastructure are also important in shaping sectoral structures and maintaining competitive advantage (Author, 2015). These considerations help explain why Automotive and Aerospace, Supply Chain and Transportation, and Advanced Manufacturing occupy high positions in the transformation-exposure rankings.

Government subsidies, industrial policies, and regulatory mechanisms also represent important components of sectoral transformation, even though Government and Public Sector does not occupy one of the highest positions in the revised rankings. Mazzucato (2018) argues that public intervention does not merely serve a regulatory function but can also assume an innovative and direction-setting role in economic transformation. In the context of the present study, the relatively lower ranking of Government and Public Sector does not mean that government policies are unimportant. Instead, it indicates that the sector's cumulative exposure across all 12 macrotrends is lower than that of sectors such as Mining and Metals, Automotive and Aerospace, and Supply Chain and Transportation.

Agriculture, Forestry and Fishing also occupies a consistently high position across the three methods. This result can be associated with the increasing importance of climate-change adaptation, sustainable production, demographic change, food security, and economic uncertainty. Reports published by the FAO emphasize the central role of sustainable agriculture in future economic and ecological transformations (FAO, 2023). Pretty (2018) similarly notes that sustainable agriculture contributes not only to environmental objectives but also to economic and social resilience. Accordingly, the high ranking of Agriculture, Forestry and Fishing indicates that the sector faces intensive and multidimensional transformation pressure arising from environmental, economic, demographic, and social macrotrends.

Insurance and Pensions Management occupies a middle-to-lower position in the revised rankings rather than ranking last. This result suggests that its cumulative exposure to the 12 macrotrends is lower than that of the leading sectors but remains higher than that of the sectors positioned at the bottom of the rankings. Furthermore, the sector may experience stronger transformation pressure over time because artificial intelligence and other digital technologies are increasingly reshaping operational processes in financial services and insurance (Davenport & Ronanki, 2018). At the bottom of the rankings, Accommodation, Food, and Leisure and Real Estate exhibit the lowest cumulative transformation-exposure levels. This does not imply that these sectors are unaffected by macrotrends or that they perform poorly. It indicates only that, relative to the other sectors and within the scope of the 12 criteria used in the study, their combined transformation-exposure values are lower.

The three MCDM methods produced highly similar sectoral rankings. Spearman correlation analysis revealed very strong, positive, and statistically significant relationships between PIV and CRADIS ($\rho = 0.984$; $p < 0.001$), CRADIS and ARTASI ($\rho = 0.968$; $p < 0.001$), and PIV and ARTASI ($\rho = 0.953$; $p < 0.001$). The highest correlation was observed between PIV and CRADIS. These findings demonstrate that the main ranking results are robust to the different mathematical structures of the methods and that the

identification of sectors with high transformation exposure does not depend on a single MCDM technique.

Studies using data from the *Future of Jobs Report* generally focus on workforce transformation, digital skills, artificial intelligence, and future occupational structures. For example, Di Nardo et al. (2022) examine the effects of digitalization and reskilling processes on labor markets, while Frey and Osborne (2017) argue that automation will reshape employment structures and occupational requirements. In contrast, the present study contributes to the literature by comparatively evaluating the cumulative exposure of sectors to multiple global macrotrends through MCDM methods. The combined use of different weighting and ranking methods provides a multidimensional and robustness-oriented assessment of sectoral transformation intensity. Furthermore, the study conceptually distinguishes transformation exposure from sectoral performance: higher scores indicate greater exposure to transformative pressures rather than greater success or superiority.

Conclusion, Limitations, and Recommendations

This study evaluates the intensity of sectoral exposure to the transformative effects of global macrotrends using Multi-Criteria Decision-Making (MCDM) methods. The analysis, based on data from the *Future of Jobs Report 2025*, demonstrates that sectors differ considerably in their cumulative exposure to macrotrend-driven transformation. Because the criterion values represent the magnitude of expected transformative impact, all 12 criteria were modeled as maximization-oriented impact criteria. Accordingly, higher scores indicate greater transformation exposure rather than better sectoral performance.

The findings show that Mining and Metals ranks first according to the PIV, CRADIS, and ARTASI methods. Automotive and Aerospace and Supply Chain and Transportation consistently occupy the second and third positions, respectively. Advanced Manufacturing, Agriculture, Forestry and Fishing, and Chemical and Advanced Materials also rank relatively highly across the methods. These results indicate that sectors closely connected to strategic raw materials, global production networks, international trade, technological development, and decarbonization pressures face particularly intensive transformation. Conversely, Accommodation, Food, and Leisure and Real Estate occupy the lowest positions. Their lower rankings do not indicate poor performance or the absence of transformation; rather, they indicate lower cumulative exposure relative to the other sectors and the specific macrotrends included in the analysis.

The analysis also reveals a very high level of agreement among the methods. The strongest positive correlation was observed between PIV and CRADIS ($\rho = 0.984$; $p < 0.001$), followed by CRADIS and ARTASI ($\rho = 0.968$; $p < 0.001$) and PIV and ARTASI ($\rho = 0.953$; $p < 0.001$). These strong and statistically significant correlations support the consistency and robustness of the sectoral rankings. Although some differences were observed among the middle-ranking sectors, the leading and lowest-ranked sectors remained largely stable. This indicates that the principal findings are not dependent on the mathematical structure of a single MCDM method.

By assessing the effects of multiple macrotrends simultaneously, the study offers a multidimensional framework for identifying sectors facing the greatest cumulative transformation pressure. The findings can assist policymakers, decision-makers, investors, and sector representatives in developing sector-specific adaptation, workforce, investment, and resilience strategies. The study also contributes to the literature as one of the limited applications that evaluates sectoral data from the *Future of Jobs Report 2025* using multiple criterion-weighting, MCDM ranking, and aggregation methods. Furthermore, it makes an important conceptual distinction between sectoral performance and transformation exposure.

The study has several limitations. First, the analysis is limited to the sectoral and macrotrend data included in the *Future of Jobs Report 2025*. Consequently, the use of different data sources, indicators, or sector classifications could produce different results. Second, the study has a cross-sectional design and covers a specific reporting period. Therefore, it does not capture changes in sectoral transformation exposure over time or enable the identification of long-term transformation trajectories.

Third, the analysis is limited to the 12 macrotrends included in the report. However, sectoral transformation may also be affected by other factors, including technological innovations, artificial intelligence applications, regional policies, energy crises, consumer behavior, cybersecurity risks, and sustainability pressures. Although the methods generally produced highly consistent rankings, their different mathematical structures resulted in some variation among the middle-ranking sectors. Thus, the results should be interpreted within the scope of the selected criteria, weighting approaches, and ranking methods.

Another limitation is that the study relies exclusively on quantitative data and MCDM methods. Expert opinions, assessments from sector representatives, and qualitative data were not incorporated into the analytical framework. Therefore, the findings provide a comparative assessment based on the numerical data reported in the *Future of Jobs Report 2025* and do not capture sector-specific experiences, institutional conditions, or contextual interpretations of the macrotrends.

Future studies could use *Future of Jobs* reports from different years to examine changes in sectoral transformation exposure over time. Comparisons across countries, regions, or income groups could also provide a more detailed understanding of how

economic, institutional, and geographical conditions shape sectoral transformation dynamics.

Future research could incorporate additional objective or subjective weighting approaches and alternative MCDM techniques to further test the robustness of the rankings. Integrating expert opinions, sector-representative assessments, interviews, or other qualitative evidence could also provide a more comprehensive interpretation of sectoral transformation processes.

Finally, the criterion set could be expanded to include variables such as artificial intelligence adoption, green transformation investments, digital-skills requirements, cybersecurity exposure, energy dependence, supply-chain vulnerability, and regulatory intensity. As digitalization and sustainability-driven transformation continue to accelerate, examining not only the exposure of sectors to macrotrends but also their adaptive capacity and resilience could make an important contribution to future strategic planning.

This research article has been licensed with Creative Commons Attribution - Non-Commercial 4.0 International License. Bu araştırma makalesi, Creative Commons Atıf - Gayri Ticari 4.0 Uluslararası Lisansı ile lisanslanmıştır.

Author Contributions

The author contributions have been declared as follows: 1st author; %50, 2nd author; %50

Acknowledgments

The author(s) did not provide acknowledgment.

Funding and Support

The author(s) did not report any funding or support information.

Conflict of Interests

The author(s) did not report any conflict of interest.

Ethics Statement

The author(s) did not report ethical committee approval as the research content does not require.

References

Ali, Z., & Yang, M. S. (2026). Symmetry Point of Criterion and Cr-IF-Rank-Sum-Based MAIRCA Model with Advanced Filtration Techniques for Reusing Greywater. *Symmetry*, *18*(2), 329.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3–30. DOI: https://doi.org/10.1257/jep.29.3.3

Azgun, G., & Akyurt, H. (2026). Measuring the Ecotourism Performance of Nature Parks Using the CRADIS Method: An Evaluation on Giresun Province. *Journal of Humanities and Tourism Research*, *16*(1), 117-134.

Ünal, E. A. (2025). Assessment of University Sustainability Performance within the UI GreenMetric 2024 Framework Using a Hybrid WENSLO–ARTASI Approach. *Journal of Economic and Social Analysis*, (1), 54-79.

Biswas, S., Khawash, N., Chatterjee, P., & Zavadskas, E. K. (2025). Preference using Root Value based on Aggregated Normalizations (PROVAN): A data-driven method for socio-economic and innovation assessment. *Socio-Economic Planning Sciences*, 102343.

Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W. W. Norton & Company. ISBN: 978-0393239355

Chatterjee, S., & Chakraborty, S. (2024). A study on the effects of objective weighting methods on TOPSIS-based parametric optimization of non-traditional machining processes. *Decision Analytics Journal*, *11*, 100451.

Chen, H. (2025). Practical Overview of Triangular Bipolar Neutrosophic Numbers for Design Effect Evaluation of Ethnic Minority Clothing: Comprehensive Guide. *Neutrosophic Sets and Systems*, *81*(1), 30.

Chen, H., & Zhang, D. (2025). Ecological Efficiency Evaluation in Petrochemical Enterprises Using Plithogenic-ARTASI Model. *Neutrosophic Sets and Systems*, *80*(1), 36.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.

Di Nardo, M., Clericuzio, M., Murino, T., & Sepe, C. (2022). Employment 5.0: The work of the future and the future of work. *Technology in Society*, 71, 102086. DOI: https://doi.org/10.1016/j.techsoc.2022.102086

Dudić, B., Van Duc, D., Son, N. H., & Ašonja, A. (2024). Comparison of MCDM methods effectiveness in the selection of plastic injection molding machines. *Teknomekanik*, *7*(1), 1-19.

Durdu, D., Akbulut, O. Y., & Aydın, Y. (2025). Evaluating Corporate Financial Performance in the Turkish Insurance Sector Using an Integrated Grey Decision-Making Framework. *Journal of Research in Economics, Politics & Finance*, *10*(3).

Erdoğan, B. (2022). Evaluation of Financial Performance of Banks Registered on BIST with AHP-SD Based PIV Method. *Pamukkale University Journal of Social Sciences Institute*, (52), 93-109.

Ersoy, N. (2021). Application of the PIV method in the presence of negative data: an empirical example from a real-world case. *Hitit Sosyal Bilimler Dergisi*, *14*(2), 318-337.

FAO. (2023). *The State of Food and Agriculture 2023*. Rome: Food and Agriculture Organization.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. DOI: https://doi.org/10.1016/j.techfore.2016.08.019

Geels, F. W. (2018). Disruption and low-carbon system transformation: Progress and new challenges in socio-technical transitions research and the Multi-Level Perspective. *Energy Research & Social Science*, 37, 224–231. DOI: https://doi.org/10.1016/j.erss.2017.10.010

Gligorić, Z., Gligorić, M., Miljanović, I., Lutovac, S., & Milutinović, A. (2023). Assessing criteria weights by the symmetry point of criterion (novel SPC method)–application in the efficiency evaluation of the mineral deposit multi-criteria partitioning algorithm. *Computer Modeling in Engineering & Sciences*, *136*(1), 955.

Goswami, S. S., Mohanty, S. K., & Behera, D. K. (2022). Selection of a green renewable energy source in India with the help of MEREC integrated PIV MCDM tool. *Materials today: proceedings*, *52*, 1153-1160.

Kahreman, Y. (2024). Determining Turkey's Sustainable Development and Sub-Dimensional Performances by LOPCOW-CRADIS Method. *MANAS Journal of Social Studies*, *13*(4), 1411-1426.

Kahreman, Y. (2026). Assessing the productive capacity performance based on an integrated MCDM model: critical insights underlying the impact of the COVID-19 pandemic. *International Journal of Productivity and Performance Management*, 1-26.

Kara, K., Yalçın, G. C., Ergin, E. A., Simic, V., & Pamucar, D. (2024). A neutrosophic WENSLO-ARLON model for measuring sustainable brand equity performance. *Socio-economic planning sciences*, *94*, 101918.

Kara, K., Ergin, E. A., Yalçın, G. C., Çelik, T., Deveci, M., & Kadry, S. (2025). Sustainable brand logo selection using an AI-Supported PF-WENSLO-ARLON hybrid method. *Expert Systems with Applications*, *260*, 125382.

Keleş, M. K., & Alaca, D. (2023). Analysis of Digital Marketing Technologies with PIV and CODAS Methods. *Mehmet Akif Ersoy Üniversitesi Uygulamalı Bilimler Dergisi*, *7*(1), 84-101.

Keleş, N., & Kahveci, A. (2025). Evaluating the logistics performance of the EU candidate and member countries using the WENSLO and ARTASI methods. *Pamukkale Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, (68), 43-66.

Khan, N. Z., Ansari, T. S. A., Siddiquee, A. N., & Khan, Z. A. (2019). Selection of E-learning websites using a novel Proximity Indexed Value (PIV) MCDM method. *Journal of Computers in Education*, *6*(2), 241-256.

Krishankumar, R., & Ecer, F. (2023). Selection of IoT service provider for sustainable transport using q-rung orthopair fuzzy CRADIS and unknown weights. *Applied Soft Computing*, *132*, 109870.

Mariana Mazzucato. (2018). *The Entrepreneurial State: Debunking Public vs. Private Sector Myths*. London: Penguin Books. ISBN: 978-0241188811

Mazzucato, M. (2018). *The Entrepreneurial State: Debunking Public vs. Private Sector Myths*. London: Penguin Books.

Mufazzal, S., & Muzakkir, S. M. (2018). A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals. *Computers & Industrial Engineering*, *119*, 427-438.

Nguyen, H. S., Hieu, T. T., Thang, N. M., Tan, H. N., Can, N. T., Thao, P. T., & Bao, N. C. (2024). Selection of crankshaft manufacturing material by the PIV method. *Engineering, Technology & Applied Science Research*, *14*(4), 14848-14853.

Pamucar, D., Ecer, F., Gligorić, Z., Gligorić, M., & Deveci, M. (2023). A novel WENSLO and ALWAS multicriteria methodology and its application to green growth performance evaluation. *IEEE Transactions on Engineering Management*, *71*, 9510-9525.

Pamucar, D., Simic, V., Görçün, Ö. F., & Küçükönder, H. (2024). Selection of the best Big Data platform using COBRAC-ARTASI methodology with adaptive standardized intervals. *Expert Systems with Applications*, *239*, 122312.

Pamucar, D., Özçalıcı, M., & Gurler, H. E. (2025). Evaluation of the efficiency of world airports using WENSLO-ARTASI and Monte Carlo simulation. *Journal of Air Transport Management*, *124*, 102749.

Pretty, J. (2018). Intensification for redesigned and sustainable agricultural systems. *Science*, 362(6417), eaav0294.

Puška, A., Stević, Ž., & Pamučar, D. (2022). Evaluation and selection of healthcare waste incinerators using extended sustainability criteria and multi-criteria analysis methods. *Environment, Development and Sustainability*, 24(9), 11195-11225.

Puška, A., Hodžić, I., & Štilić, A. (2023). Evaluating the knowledge economies within the European Union: A global knowledge index ranking via entropy and CRADIS methodologies. *International Journal of Knowledge and Innovation Studies*, *1*(2), 103-115.

Puška, A., Štilić, A., & Stojanović, I. (2023). Approach for multi-criteria ranking of Balkan countries based on the index of economic freedom. *Journal of Decision Analytics and Intelligent Computing*, *3*(1), 1-14.

Sovacool, B. K., Hook, A., Martiskainen, M., & Brock, A. (2020). The decarbonisation divide: Contextualizing landscapes of low-carbon exploitation and toxicity in Africa. *Global Environmental Change*, 60, 102028.

Stojanović, I. (2024). Selection of a green contractor for the implementation of a solar power plant project. *Symmetry*, *16*(4), 441.

Subramanian, S. P., Pandian, P., Sivaprakasam, R., & Kadarkarai, J. (2025). A Novel Machine Learning Framework for Optimized Supplier Selection Using the Weights by ENvelope and SLOpe (WENSLO) Technique. *Applied Operations and Analytics*, *1*(1), 1-10.

Şahin, Ş. U., & Özdemir, A. (2025). Evaluatıon Of The Macroeconomıc Performances of G8 Countrıes Wıth The CRITIC and CRADIS Multi Criteria Decision Making Method. *Yönetim Bilimleri Dergisi*, *23*(55), 382-405.

Taşcı, M. Z. (2025). SD SPC ARTASI Optimal Portfolio Selection with the Integrated CKKV Model: An Application in the BIST Automotive Sector. *Internatıonal Journal of Fınancıal Economıcs And Bankıng Practıces*, *6*(1), 153-176.

Trung, D. D., Thinh, H. X., & Ha, L. D. (2022). Comparison of the RAFSI and PIV method in multi-criteria decision making: application to turning processes. *International Journal of Metrology and Quality Engineering*, *13*, 14.

Yarlıkaş, S. (2025). Assessment of Knowledge-Oriented Development Levels of Northern European Countries by WENSLO Based ARAS Method. *Premium e-Journal of Social Sciences (PEJOSS)*, *9*(61), 1630-1642.

Van Dua, T., Van Duc, D., Bao, N. C., & Trung, D. D. (2024). Integration of objective weighting methods for criteria and MCDM methods: application in material selection. *EUREKA: Physics and Engineering*, (2), 131-148.

Wang, J., Setiawansyah, S., Ardiansah, T., Ulum, F., & Sumanto, S. (2026). Decision Support System for Determining Strategic Warehouse Locations Using a Combination of the WENSLO Weighting and RAWEC Method. *JUTI: Jurnal Ilmiah Teknologi Informasi*, 165-184.

World Economic Forum. (2025). *Future of Jobs Report 2025*. Geneva: World Economic Forum. Resmî bağlantı: Future of Jobs Report 2025

IEA – World Energy Outlook 2024

World Economic Forum – Future of Jobs Report 2025

International Energy Agency. (2024). *World Energy Outlook 2024*. Paris: IEA. Resmî bağlantı: IEA World Energy Outlook 2024

Appendix 1. Mathematical Steps and Formulas

WENSLO METHOD	
Step 1: Creating a decision matrix	$[\zeta_{ij}]_{mxn}$
Step 2: Obtaining the normalized decision matrix	$z_{ij} = \frac{\zeta_{ij}}{\sum_{i=1}^{m} \zeta_{ij}}$
Step 3: Calculation of the criterion class interval	$\Delta z_j = \frac{max z_{ij} - min z_{ij}}{1 + 3.322 * \log(m)}$
Step 4: Calculation of the criterion slope	$tan\varphi_j = \frac{\sum_{i=1}^{m} z_{ij}}{(m-1) * \Delta z_j}$
Step 5: Calculation of the criterion envelope	$E_j = \sum_{i=1}^{m-1} \sqrt{(z_{i+1,j} - z_{i,j})^2 + \Delta z_j{}^2}$
Step 6: Calculate of the envelope–slope ratio	$q_j = \frac{E_j}{tan\varphi_j}$
Step 7: Calculation of criterion weights	$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j}$
SPC METHOD	
Step 1: Creating a decision matrix	$DM = \lvert x_{ij} \rvert_{mxn}$
Step 2: Calculate the symmetry point of criterion	$SPC_j = \frac{min\{x_{ij}\} + max\{x_{ij}\}}{2}$

Step 3: Creating absolute distance matrix	$D = \left\|\left\|d_{ij}\right\|\right\|_{mxn} = \begin{vmatrix} \|x_{11} - SPC_1\| & \|x_{12} - SPC_2\| & \dots & \|x_{1n} - SPC_n\| \\ \|x_{21} - SPC_1\| & \|x_{22} - SPC_2\| & \dots & \|x_{2n} - SPC_n\| \\ \vdots & \vdots & \ddots & \vdots \\ \|x_{m1} - SPC_1\| & \|x_{m2} - SPC_2\| & \dots & \|x_{mn} - SPC_n\| \end{vmatrix}$
Step 4: Construction of a matrix of symmetry modules	$R = \left\|r_{ij}\right\|_{mxn} = \begin{vmatrix} \frac{\sum_{i=1}^{m} d_{i1}}{m} / x_{11} & \frac{\sum_{i=1}^{m} d_{i2}}{m} / x_{12} & \dots & \frac{\sum_{i=1}^{m} d_{in}}{m} / x_{11} \\ \frac{\sum_{i=1}^{m} d_{i1}}{m} / x_{21} & \frac{\sum_{i=1}^{m} d_{i2}}{m} / x_{22} & \dots & \frac{\sum_{i=1}^{m} d_{in}}{m} / x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\sum_{i=1}^{m} d_{i1}}{m} / x_{m1} & \frac{\sum_{i=1}^{m} d_{i2}}{m} / x_{m2} & \dots & \frac{\sum_{i=1}^{m} d_{in}}{m} / x_{mn} \end{vmatrix}$
Step 5: Calculation of the symmetry modulus of the criterion	$Q = \left\|q_{1j}\right\|_{1xn} = \left\|\frac{\sum_{i=1}^{m} r_{i1}}{m} \quad \frac{\sum_{i=1}^{m} r_{i2}}{m} \quad \dots \quad \frac{\sum_{i=1}^{m} r_{in}}{m}\right\|$
Step 6: Calculation of criterion weights	$W = \left\|w_{1j}\right\|_{1xn} = \left\|\frac{q_1}{\sum_{j=1}^{n} q_j} \quad \frac{q_2}{\sum_{j=1}^{n} q_j} \quad \dots \quad \frac{q_j}{\sum_{j=1}^{n} q_j}\right\|$
PIV METHOD	
Step 1: Construction of the decision matrix	$DM = \left\|x_{ij}\right\|_{mxn}$
Step 2: Obtaining the normalized decision matrix	$r_i = \frac{x_i}{\sqrt{\sum_{i=1}^{m} x_i^2}}$
Step 3: Obtaining the weighted normalized matrix	$v_i = w_j * r_i$
Step 4: Evaluation of weighted proximity index	$u_i = v_{max} - v_i$ for benefit attribute $u_i = v_i - v_{max}$ for cost attribute
Step 5: Determination of overall proximity value	$d_i = \sum_{j=1}^{n} u_j$
CRADIS METHOD	
Step 1: Construction of the decision matrix	$DM = \left\|x_{ij}\right\|_{mxn}$
Step 2: Normalization of decision matrix	$n_{ij} = \frac{x_{ij}}{x_{jmax}}$ $n_{ij} = \frac{x_{jmin}}{x_{ij}}$
Step 3: Obtaining the weighted normalized matrix	$v_{ij} = w_j * n_{ij}$
Step 4: Determining the ideal and anti-ideal solution	$t_i = max v_{ij}$ $t_{ai} = min v_{ij}$
Step 5: Calculation of deviations from ideal and anti-ideal solutions	$d^+ = t_i - v_{ij}$ $d^- = v_{ij} - t_{ai}$
Step 6: Calculating the degree to which alternatives deviate from ideal and anti-ideal solutions	$s_i^+ = \sum_{j=1}^{n} d^+$ $s_i^- = \sum_{j=1}^{n} d^-$
Step 7: Calculation of the utility function	$K_i^+ = \frac{s_0^+}{s_i^+}$

	$K_i^- = \frac{s_i^-}{s_0^-}$
Step 8: Ranking alternatives	$Q_i = \frac{K_i^+ + K_i^-}{2}$
ARTASI METHOD	
Step 1: Construction of the decision matrix	$DM = \left\|\wp_{ij}\right\|_{mxn}$
Step 2: Defining absolute minimum and maximum values	$\wp_j^{max} = \max_{1\le i\le m}(\wp_{ij}) + \left\{\max_{1\le i\le m}(\wp_{ij})\right\}^{1/m}$ *for absolute maximum values* $\wp_j^{min} = \min_{1\le i\le m}(\wp_{ij}) + \left\{\min_{1\le i\le m}(\wp_{ij})\right\}^{1/m}$ *for absolute minimum values*
Step 3: Standardization of the initial decision matrix	$\phi_{ij} = \frac{\psi^{(u)} - \psi^{(l)}}{\wp_j^{max} - \wp_j^{min}}\wp_{ij} + \frac{\wp_j^{max}.\psi^{(l)} - \wp_j^{min}.\psi^{(u)}}{\wp_j^{max} - \wp_j^{min}}$ $\zeta_{ij} = -\phi_{ij} + \max_{1\le i\le m}(\phi_{ij}) + \min_{1\le i\le m}(\phi_{ij})$
Step 4: Calculating the usefulness of alternatives to ideal and anti-ideal values	$\vartheta_{ij}^+ = \frac{\zeta_{ij}}{\max_{1\le i\le m}(\zeta_{ij})}.w_j.\psi^{(u)}$ *ideal value* $\vartheta_{ij} = \frac{\min_{1\le i\le m}(\zeta_{ij})}{\zeta_{ij}}.w_j.\psi^{(u)}$ $\vartheta_{ij}^- = -\vartheta_{ij}^- + \max_{1\le i\le m}(\vartheta_{ij}) + \min_{1\le i\le m}(\vartheta_{ij})$ *anti ideal value*
Step 5: Calculating the overall utility levels of the alternatives	$\Im_i^+ = \sum_{j=1}^n \vartheta_{ij}^+$ *for ideal value* $\Im_i^- = \sum_{j=1}^n \vartheta_{ij}^-$ *for anti ideal value*
Step 6: Calculation of final utility functions and ranking of alternatives	$\Omega_i = (\Im_i^+ + \Im_i^-)\{a.f(\Im_i^+)^\varphi + (1-a).f(\Im_i^-)^\varphi\}^{\frac{1}{\varphi}}; \varphi \in [1,+\infty); a \in [0,1]$ $\Omega_i = (\Im_i^+ + \Im_i^-)\{0.5.f(\Im_i^+) + 0.5.f(\Im_i^-)\}$ *for* $\varphi = 1$ *and* $a = 0.5$
BORDA	
Step 1: Obtaining the order from the methods	$rank_i$
Step 2: Point conversion	$Borda_i = n - rank_i + 1$
Step 3: Final ranking will be created based on the total score	The ranking is based on total hull points.