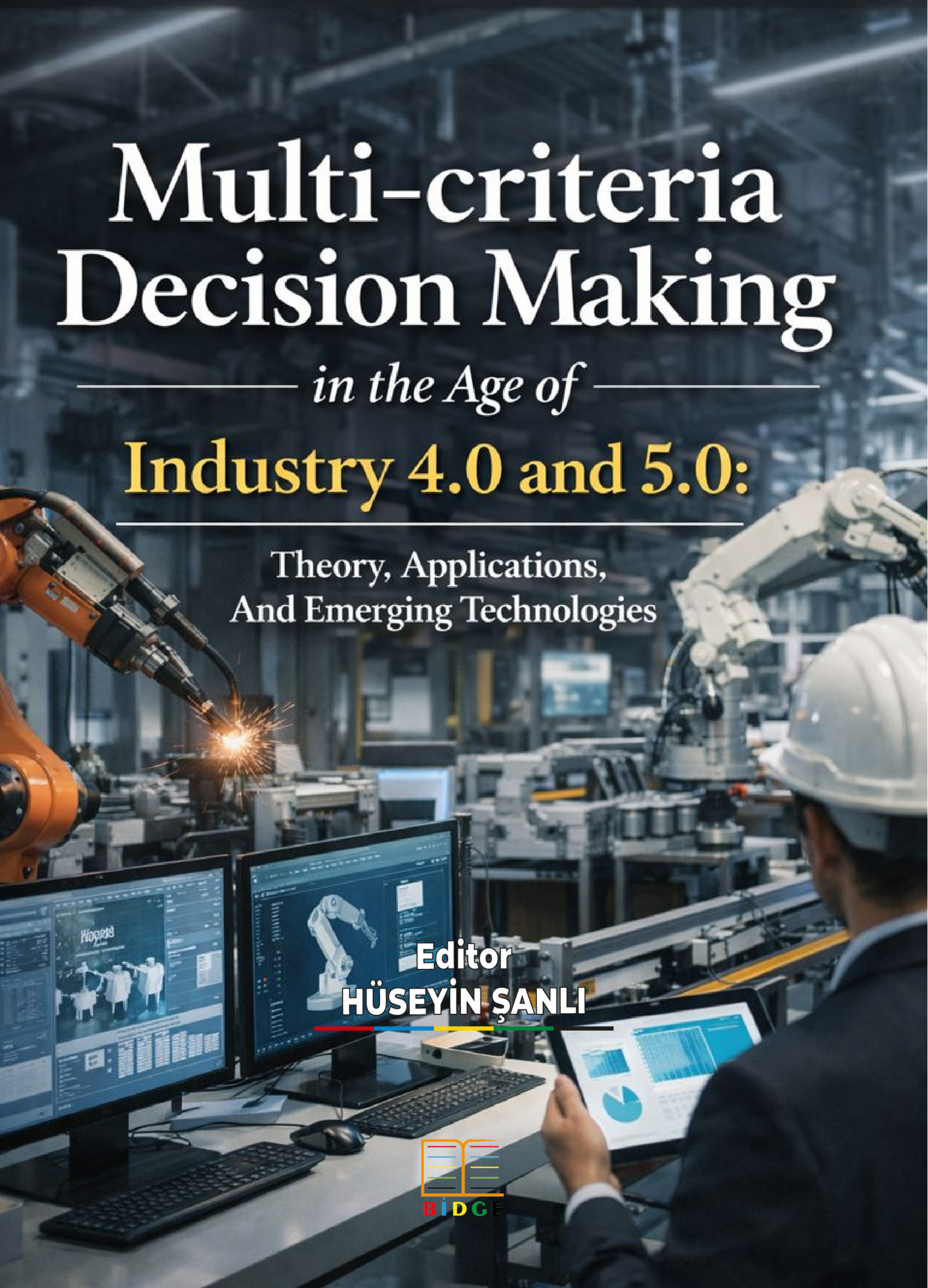

Multi-criteria Decision Making

in the Age of

Industry 4.0 and 5.0:

Theory, Applications, And Emerging Technologies

Editor
HÜSEYİN ŞANLI

BİDGE

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Multi-criteria Decision Making in the Age of Industry 4.0 and 5.0: Theory, Applications, And Emerging Technologies

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Foreword

The transition toward Industry 4.0 and the emerging vision of Industry 5.0 has profoundly transformed decision-making environments across industrial and societal systems. The increasing integration of digital technologies, intelligent automation, and human-centered design principles has amplified the complexity, uncertainty, and multidimensionality of contemporary decision problems. In this context, Multi-Criteria Decision Making (MCDM) provides a rigorous and systematic framework for evaluating alternatives involving conflicting objectives and diverse stakeholder perspectives.

While Industry 4.0 emphasizes data-driven efficiency and technological integration, Industry 5.0 extends this paradigm by highlighting sustainability, resilience, and human-centric values. Addressing such intertwined technological and societal challenges requires advanced decision models capable of combining quantitative data, expert knowledge, and qualitative judgments. MCDM methodologies, including classical, fuzzy, hybrid, and AI-enhanced approaches, play a critical role in supporting transparent, robust, and informed decisions within these evolving industrial landscapes.

This book offers a concise yet comprehensive perspective on the theoretical foundations, applications, and emerging technologies of MCDM in the age of Industry 4.0 and 5.0. It is intended to serve as a valuable reference for researchers, practitioners, and decision-makers seeking to design intelligent, sustainable, and human-oriented systems for the next generation of industry.

İÇİNDEKİLER

CHAPTER 1

DAIRY CATTLE SELECTION WITH THE PICTURE FUZZY INTERACTIONAL BONFERRONI MEAN METHOD

HALİL ŞEN[1]

Introduction

In dairy farming, selecting the right breed is a strategic decision that determines not only the short-term milk production of the operation but also its long-term profitability, herd sustainability, and adaptability to environmental conditions. In the breed selection process, criteria such as feed utilization, reproductive performance, health indicators, and herd duration play a critical role, as well as milk yield and milk components. However, these criteria often interact with each other, and an improvement in one criterion may lead to unexpected results in another. For example, the goal of high milk yield requires evaluation in conjunction with indirect effects such as increased metabolic load, decreased fertility, or increased health problems. Therefore, selecting the right breed is not a choice based on a single performance indicator, but rather a multi-criteria decision-making problem in which numerous criteria are considered

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simultaneously. Comparative studies in the literature on Holstein-Friesian, Jersey, and their hybrids show that the performance of the breeds varies significantly depending on the breeding system and farm objectives. Focusing on economic and production performance, Ahlborn & Bryant (1992), compared Holstein-Friesian and Jersey cows, revealing that not only production but also optimum herd density and economic outcomes differed between breeds; they emphasized that breed selection directly affects farm profitability. Regarding production efficiency and energy metabolism, L'Huillier et al. (1988) and Mackle et al. (1996) stated that energy use dynamics, pasture uptake capacity, and feed conversion efficiency differed in Jersey and Friesian cows during the early lactation period; therefore, in breed comparisons, not only milk quantity but also energy balance and productivity indicators should be included in the decision-making process. Similarly, Thomson et al. (2001) demonstrated the effect of the lactation phase on pasture-milk conversion efficiency, showing that the production patterns of the breeds differed throughout the year. These findings indicate that limiting breed selection to a "milk yield per cow" approach may lead to incomplete results. In determining the right breed, reproductive performance, herd survival, and functional characteristics are just as important as production. Dillon et al. (2003), comparing the reproduction and survival of different breeds in pasture-based seasonal systems, reported significant differences between breeds and hybrids. Lucy (2001), emphasizing that fertility losses can become a structural problem in high-yielding herds, revealed that breed selection and breeding goals should be designed to be sensitive not only to increased production but also to reproductive success. Heins et al. (2008) and Auldist et al. (2007), evaluating pure Holstein and Jersey×Holstein hybrids, showed that hybridization can provide advantages in functional areas such as fertility and early lactation performance. In terms of genetic structure, Ahlborn-Breier and Hohenboken (1991) and McAllister et al. (1994) highlighted the importance of additive and non-additive genetic effects on milk production and lifetime profitability, and stated that heterosis effects should be considered in breed selection decisions. In the health dimension, Berry et al. (2006) and Washburn et al. (2002) showed that indicators such as somatic cell count, mastitis, and body condition vary depending on the breed and breeding system, making it necessary to evaluate breed selection together with health outcomes. Prendiville et al. (2009; 2010), who linked production efficiency in pasture-based systems to behavior and intake capacity, emphasized that pasture use efficiency and production strategies differ among breeds and that breed selection should also be considered with system-level measures such as output per hectare. When these studies are evaluated together, it is concluded that dairy cattle breed selection; It is observed that decision-making problems requiring the simultaneous consideration of numerous criteria such as production, productivity, reproduction, health, genetic makeup, and economic outcomes, where there are significant interactions between criteria and considerable uncertainty, are prevalent. However, in practice, decision-makers struggle to quantify many criteria simultaneously, and expert evaluations often appear as linguistic expressions (such as high, medium, low) or judgments expressing hesitation. This situation increases the need for advanced decision support methods that can adequately represent both uncertainty and the interactions between criteria. In this context, the Picture Fuzzy Set (PF) approach is particularly useful in high-uncertainty situations such as breed selection, because it allows decision-makers to represent their evaluations not only with "acceptance" and "rejection" levels but also with a "neutrality/undecided" component.

It offers a strong modeling advantage in problems where the criteria are not independent. In addition, the Bonferroni mean operator has a structure that can perform aggregation by considering interactions when the criteria are not independent. The Picture Fuzzy Interactional Bonferroni Mean (PF-IBM) method, which integrates these two approaches, allows both the modeling of expert hesitations in a picture fuzzy structure and the inclusion of inter-criteria interactions in the aggregation process. Therefore, PF-IBM offers a suitable methodological framework for more realistically evaluating multidimensional performance and determining the most suitable breed for the conditions in the dairy cattle breed selection problem. In this study, dairy cattle breeds such as Holstein-Friesian, Jersey, and hybrid alternatives are analyzed using the PF-IBM method under a set of criteria including production, productivity, reproduction, health, and economic criteria, with the aim of obtaining an integrated performance ranking of the alternatives.

Method

Decision-making problems in real-world applications are often characterised by imprecision, hesitation, and complex interdependencies among evaluation criteria, which limit the effectiveness of classical and conventional fuzzy multi-criteria decision-making (MCDM) approaches. In many practical settings, decision makers are unable to express their preferences using precise numerical values and instead rely on partial, hesitant, or even conflicting judgments. Moreover, evaluation criteria frequently interact with one another, exhibiting complementary or antagonistic relationships that cannot be adequately captured by aggregation operators assuming criterion independence. To address these challenges, this study adopts the Picture Fuzzy Interactional Bonferroni Mean (PFIBM) method, which integrates the expressive power of picture fuzzy sets with the interaction-sensitive structure of the Bonferroni mean. By simultaneously modelling membership, non-membership, and abstention degrees, while explicitly accounting for pairwise criterion interactions, PFIBM provides a robust and realistic aggregation framework for decision-making under uncertainty. Consequently, the method is particularly suitable for complex evaluation problems where uncertainty and interdependence among criteria play a critical role.

Picture Fuzzy Sets (PFS) go beyond classical and intuitive fuzzy approaches by modeling uncertainty through a three-component structure. In the PFS approach, introduced by Cường (2014), the evaluation of an alternative according to a criterion is not limited to "acceptance/membership" and "rejection/non-membership"; the abstention component, representing the decision-maker's hesitation, is also explicitly defined. This three-component structure provides a more realistic representation, especially in decision problems where expert evaluations lack complete certainty and the "neither positive nor negative" range is high. Therefore, PFS offers an important theoretical foundation that allows for a more detailed examination of uncertainty and indecision in the multi-criteria decision-making (MCDM) literature (Cường, 2014).

One of the key issues in PFS-based MCDM studies is the development of aggregation operators that can transform evaluations under numerous criteria into a single integrated result. In this context, Zhang and Xu (2021) developed and applied picture-fuzzy interactive aggregation operators to the risk assessment problem, demonstrating that the “interaction” component significantly affects the results when the criteria are not independent of each other. Similarly, Liu, Chen, and Wang (2022) applied a multi-attribute decision-making model based on interactive aggregation operators in a PFS environment to the supplier selection problem; thus, they revealed both the uncertainty/hesitation modeling power of PFS and the performance of operators including interaction in practical decision problems. These studies emphasize that in PFS-based decision models, it is critical to include not only the representation of uncertainty but also the complementary or weakening relationships between criteria in the aggregation structure (Liu et al., 2022; Zhang & Xu, 2021).

One of the operators that systematically handles the concept of interaction is the Bonferroni mean family. Due to its structure that considers the reciprocal relationship between pairs of criteria, the Bonferroni mean provides a more flexible aggregation compared to additive weighting approaches where the criteria are assumed to be independent. In this context, Xu, Yager, and Liu (2019) discussed Bonferroni mean extensions for decision-making under uncertainty, examining the adaptability of the operator to different decision environments and the theoretical justifications for interaction-based aggregation. Combining the Bonferroni approach with PFS represents a more advanced methodological line that addresses both triple uncertainty (membership–counter-membership–abstention) and inter-criterion interaction under the same framework (Cường, 2014; Xu et al., 2019).

One current and powerful example of this developmental line is the Picture Fuzzy Interaction Bonferroni Mean (PFIBM) operators. Liu, Wu, and Chen (2023) clarified the theoretical framework and formally presented the fundamental properties of PFIBM operators (e.g., commutativeness, monotonicity, and boundary conditions) by defining them under strict triangular norms. Furthermore, by proposing weighted and normalized versions of PFIBM, its applicability to real decision problems has been strengthened, and the effectiveness of the method in multi-criteria decision-making applications has been demonstrated (Liu, Wu, & Chen, 2023). Therefore, the PFIBM literature offers an advanced decision support framework that aims to produce more consistent and realistic decision outcomes in problems where the criterion independence assumption is weak, by integrating the triple uncertainty modeling capacity of PFS with the interaction-sensitive structure of the Bonferroni approach (L. Liu et al., 2023; P. Liu et al., 2022; Xu et al., 2019; Zhang & Xu, 2021).

Picture Fuzzy Interactional Bonferroni Mean (PFIBM) Method

Preliminaries and Notation:

Let $A = \{A_1, A_2, \dots, A_m\}$ denote the set of alternatives and $C = \{C_1, C_2, \dots, C_n\}$ the set of evaluation criteria.

In the picture fuzzy environment, the evaluation of alternative A_i with respect to criterion C_j is expressed as a picture fuzzy number (PFN)

$$\tilde{x}_{ij} = (\mu_{ij}, \vartheta_{ij}, \pi_{ij}),$$

where μ_{ij}, ϑ_{ij}, and π_{ij} represent the degrees of membership, non-membership, and abstention, respectively, satisfying

$$0 \leq \mu_{ij} + \vartheta_{ij} + \pi_{ij} \leq 1.$$

Let $\mathbf{w} = (w_1, w_2, \dots, w_n)$ be the criterion weight vector, where

$$w_j \geq 0 \text{ and } \sum_{j=1}^{n} w_j = 1.$$

- Step 1: Normalization

The original decision matrix is normalized according to the benefit or cost nature of the criteria to ensure comparability across different measurement scales. After normalization, all criteria are transformed into benefit-type values.

- Step 2: Construction of the Picture Fuzzy Decision Matrix

Normalized values are converted into picture fuzzy numbers using predefined linguistic scales or expert elicitation procedures, forming the picture fuzzy decision matrix

$$\tilde{X} = [\tilde{x}_{ij}]_{m \times n}.$$

Step 3: Determination of Criterion Weights

Criterion weights are obtained either from subjective expert judgments or objective methods such as the Preference Selection Index (PSI). The resulting weight vector reflects the relative importance of each criterion in the decision problem.

- Step 4: Aggregation Using the PFIBM Operator

The core of the methodology lies in aggregating the picture fuzzy evaluations using the Picture Fuzzy Interactional Bonferroni Mean (PFIBM) operator. Unlike classical aggregation operators, PFIBM explicitly accounts for interactions among criteria, rather than assuming their independence.

For an alternative A_i, the PFIBM operator aggregates the set of PFNs $\{\tilde{x}_{i1}, \tilde{x}_{i2}, \dots, \tilde{x}_{in}\}$ by considering all pairwise criterion combinations. The general PFIBM formulation is expressed as

$$PFIBM(\tilde{x}_{i1}, \dots, \tilde{x}_{in}) = \left(\frac{1}{n(n-1)} \bigoplus_{j \neq k} \left(\tilde{x}_{ij}^{\alpha} \otimes \tilde{x}_{ik}^{\beta}\right)\right)^{\frac{1}{\alpha+\beta}},$$

where

- $\otimes$and $\oplus$denote interactional multiplication and addition operators defined in the picture fuzzy domain,
- $\alpha, \beta > 0$are interaction parameters controlling the strength of pairwise effects, and
- all ordered pairs (j, k), $j \neq k$, are considered.

This structure allows complementary (synergistic) or weakening (antagonistic) relationships between criteria to influence the aggregated result.

When criterion importance is incorporated, the weighted PFIBM operator is defined as

$$W\text{-}PFIBM(\tilde{x}_{i1}, \dots, \tilde{x}_{in}) = \left(\bigoplus_{j \neq k} \left((w_j \tilde{x}_{ij})^{\alpha} \otimes (w_k \tilde{x}_{ik})^{\beta} \right) \right)^{\frac{1}{\alpha+\beta}}$$

This formulation ensures that criteria with higher weights exert greater influence on the aggregation outcome while preserving the interactional structure.

To guarantee comparability across alternatives, a normalized PFIBM formulation can be applied by scaling the aggregated PFNs so that the resulting membership, non-membership, and abstention degrees remain within $[0, 1]$and satisfy the PFS constraint. This step is particularly important when PFIBM is combined with different weighting or normalization strategies.

The parameters $\alpha$and βregulate the intensity of criterion interactions:

- $\alpha = \beta = 1$: symmetric interaction, commonly used as a neutral baseline;
- $\alpha > \beta$: emphasizes the dominant effect of one criterion over another;
- $\beta > \alpha$: highlights secondary or moderating effects.

In practical applications, parameter values are selected based on expert judgment, sensitivity analysis, or robustness testing to ensure stable ranking results.

- Step 5: Ranking Using the Score Function

For each alternative, the aggregated PFN

$$\tilde{A}_i = (\mu_i, \vartheta_i, \pi_i)$$

is converted into a crisp value using the score function

$$S(\tilde{A}_i) = \mu_i - \vartheta_i.$$

A higher score indicates superior overall performance. Alternatives are ranked in descending order of their score values.

Application and Findings

This study applies an integrated expert-based weighting–PFIBM decision-making framework to evaluate dairy cattle breeds suitable for the Western Mediterranean Region, where climatic stress, feed costs, and sustainability constraints play a decisive role in dairy production systems. The application phase consists of three main stages: (i) determination of criterion weights based on expert judgment, (ii) definition of alternatives and evaluation criteria, and (iii) construction of picture fuzzy decision matrices for PFIBM-based aggregation.

In contrast to objective weighting schemes (e.g., PSI), this study adopts an expert judgment–based weighting approach to assign the relative importance of evaluation criteria. This choice is motivated by the fact that dairy cattle breed selection is a domain-specific decision problem in which the practical relevance of criteria depends strongly on regional climatic conditions, production constraints, and sectoral priorities. Therefore, criterion weights were determined through a structured expert consensus process considering the definitions of the criteria, their economic and biological implications, and their expected impact under Western Mediterranean conditions (e.g., heat stress and feed-cost pressure).

In this study, evaluations were conducted by a panel of five decision makers with complementary academic and practical expertise in dairy production systems. The diversity of the decision-making group was intended to ensure a comprehensive assessment of both productive and environmental aspects of dairy cattle breed selection.

The decision makers involved in the evaluation process are defined as follows:

- D1: Animal Science Professor, specializing in dairy cattle breeding and production systems
- D2: Veterinarian, with expertise in animal health, disease resistance, and udder health
- D3: Farm Manager, responsible for operational management and on-farm performance evaluation
- D4: Feed and Nutrition Specialist, focusing on feed efficiency and nutritional performance
- D5: Dairy Processing and Milk Quality Specialist, emphasizing milk composition and processing suitability

To avoid subjective bias and to ensure neutrality among expert opinions, all decision makers were assigned equal importance in the aggregation process. These weights were applied during the construction of the group picture fuzzy decision matrix.

The picture fuzzy decision matrices obtained from each decision maker were then aggregated using these equal weights, and the resulting group evaluations were subsequently processed using the PFIBM operator.

This design ensures that (i) criterion importance reflects domain knowledge and regional production realities through expert-based weighting, while (ii) the aggregation of expert judgments remains unbiased by treating all decision makers equally in the group decision-making phase.

Alternatives: This study evaluates six dairy cattle breeds that are widely used or strategically important for dairy production in the Western Mediterranean Region of Turkiye. The selected breeds represent both high-yield commercial types and resilient, locally adapted genetic resources, enabling a balanced assessment of productivity and sustainability.

- A1: Holstein: Holsteins are globally dominant due to their high milk yield. However, they are highly sensitive to heat stress, which can negatively affect feed intake, fertility, and productivity in hot and humid regions unless advanced management systems are applied.
- A2: Jersey: Jersey cows produce milk with high fat and protein content and exhibit excellent feed efficiency and fertility. Their superior heat tolerance makes them particularly suitable for warm climates such as the Western Mediterranean.
- A3: Brown Swiss: Brown Swiss cattle are robust, long-lived, and environmentally adaptable. Although their milk yield is moderate, high casein content and stable performance make them suitable for diverse production systems.
- A4: Montbéliarde: This French dual-purpose breed is valued for its high-protein milk, good fertility, and calving ease. Its strong functional traits compensate for lower milk yield compared to Holsteins.
- A5: Simmental: Simmental is a dual-purpose breed offering moderate milk yield, good adaptability, and flexibility for combined milk–meat systems, particularly in transitional climatic regions.
- A6: Anatolian Black: Anatolian Black cattle are highly resilient to harsh environmental conditions. Despite low milk yield, they require minimal inputs and play an important role in sustainable and low-input dairy systems.

Evaluation Criteria: Ten criteria were used to assess the dairy cattle breeds, integrating quantitative indicators with qualitative sustainability attributes modelled using Picture Fuzzy Sets (PFS).

- C1: Milk Yield (L/day) – primary economic performance indicator.
- C2: Milk Fat (%) – key quality parameter for dairy processing.
- C3: Feed Conversion Ratio (L milk/kg feed) – reflects economic efficiency.
- C4: Fertility Rate (%) – essential for herd sustainability.
- C5: Disease Resistance (PFS) – indicates genetic and health robustness.
- C6: Udder Health (PFS) – critical for milk hygiene and mastitis control.
- C7: Heat Tolerance (PFS) – vital under hot and humid climatic conditions.
- C8: Calf Survival Rate (%) – reflects maternal capacity and genetic strength.
- C9: Local Climate Adaptation (PFS) – overall adaptability to regional conditions.
- C10: Milk Protein (%) – important for cheese yield and nutritional value.

Here, data related to quantitative criteria were normalized and then converted to PFS (Picture fuzzy sets) format with the help of scale and expert judgment, and decision matrices were created for each decision-maker. Two of these decision matrices are given as examples in Table 1 and Table 2.

Table 1. D1 (Animal Science Professor) PFS Decision Matrix

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.30; 0.10; 0.55)	(0.30; 0.10; 0.55)	(0.30; 0.10; 0.55)	(0.30; 0.10; 0.55)	(0.50; 0.10; 0.35)	(0.30; 0.10; 0.55)	(0.50; 0.10; 0.35)
A2	(0.70; 0.10; 0.20)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.85; 0.05; 0.10)
A3	(0.70; 0.10; 0.20)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)
A4	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)
A5	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.70; 0.10; 0.20)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)
A6	(0.10; 0.10; 0.75)	(0.70; 0.10; 0.20)	(0.30; 0.10; 0.55)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)

Table 2. D3 (Farm Manager) PFS Decision Matrix

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.30; 0.10; 0.55)	(0.30; 0.10; 0.55)	(0.30; 0.10; 0.55)	(0.10; 0.10; 0.75)	(0.50; 0.10; 0.35)	(0.10; 0.10; 0.75)	(0.50; 0.10; 0.35)
A2	(0.70; 0.10; 0.20)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.85; 0.05; 0.10)
A3	(0.70; 0.10; 0.20)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)
A4	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)
A5	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.85; 0.05; 0.10)	(0.70; 0.10; 0.20)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)
A6	(0.10; 0.10; 0.75)	(0.70; 0.10; 0.20)	(0.30; 0.10; 0.55)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)

These decision matrices were then combined to create a decision matrix for the group as shown in Table 3.

Table 3. Group Decision Matrix

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.82; 0.06; 0.12)	(0.46; 0.10; 0.39)	(0.46; 0.10; 0.39)	(0.30; 0.10; 0.55)	(0.26; 0.10; 0.59)	(0.26; 0.10; 0.59)	(0.26; 0.10; 0.59)	(0.50; 0.10; 0.35)	(0.26; 0.10; 0.59)	(0.46; 0.10; 0.39)
A2	(0.70; 0.10; 0.20)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.66; 0.10; 0.23)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.85; 0.05; 0.10)
A3	(0.70; 0.10; 0.20)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.73; 0.09; 0.18)
A4	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.54; 0.10; 0.32)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.73; 0.09; 0.18)
A5	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.54; 0.10; 0.32)	(0.50; 0.10; 0.35)	(0.70; 0.10; 0.20)	(0.50; 0.10; 0.35)	(0.73; 0.09; 0.18)	(0.70; 0.10; 0.20)	(0.73; 0.09; 0.18)	(0.50; 0.10; 0.35)
A6	(0.10; 0.10; 0.75)	(0.70; 0.10; 0.20)	(0.34; 0.10; 0.51)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.54; 0.10; 0.32)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.85; 0.05; 0.10)	(0.50; 0.10; 0.35)

Criterion weights were assigned based on expert judgment, taking into account regional climatic conditions, sustainability considerations, and long-term productivity. In particular, heat tolerance (C7) and local adaptability (C9) were given higher importance due to their critical role in mitigating heat stress and ensuring stable performance in the Western Mediterranean climate. The resulting criterion weight vector is given in Table 4.

Table 4. Criteria and Their Weights

Code	Criterion	Weight
C1	Milk Yield	0.10
C2	Milk Fat Content	0.08
C3	Feed Conversion Efficiency	0.12
C4	Fertility Rate	0.10
C5	Disease Resistance	0.10
C6	Udder Health	0.07
C7	Heat Tolerance	0.18
C8	Calf Survival Rate	0.07
C9	Local Adaptability	0.15
C10	Milk Protein Content	0.03
Total		1.00

In order to obtain the final ranking of alternatives, a Bonferroni-based interaction aggregation was employed under the symmetric case ($p = q = 1$). This procedure allows the interaction among criteria to be taken into account rather than assuming full independence.

For each alternative $i$and criterion j, the picture fuzzy number

$$\tilde{x}_{ij} = (\mu_{ij}, \eta_{ij}, \nu_{ij})$$

was transformed into a crisp score using the score function:

$$S_{ij} = \mu_{ij} - \nu_{ij}$$

where $S_{ij} \in [-1,1]$.

This matrix is given in Table 5.

Table 5. Score Matrix

Alt	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.70	0.07	0.07	-0.25	-0.33	-0.33	-0.33	0.15	-0.33	0.07
A2	0.50	0.75	0.75	0.50	0.15	0.43	0.75	0.15	0.15	0.75
A3	0.50	0.50	0.15	0.15	0.50	0.50	0.15	0.50	0.15	0.55
A4	0.15	0.50	0.22	0.50	0.15	0.50	0.15	0.50	0.15	0.55
A5	0.15	0.50	0.22	0.15	0.50	0.15	0.55	0.50	0.55	0.15
A6	-0.65	0.50	-0.17	0.75	0.75	0.22	0.75	0.75	0.75	0.15

To ensure comparability and non-negativity, the scores were linearly transformed into the interval [0، 1]as follows:

$$x_{ij} = \frac{S_{ij} + 1}{2}$$

This transformation preserves the ordinal information of the scores while ensuring compatibility with the Bonferroni aggregation operator.

Each normalized score was multiplied by its corresponding criterion weight w_j:

$$y_{ij} = w_j \cdot x_{ij}$$

where

$$\sum_{j=1}^{n} w_j = 1$$

and $n$denotes the number of criteria.

Bonferroni-Based Interaction Aggregation ($p = q = 1$). The overall performance score of alternative $i$was calculated using the Bonferroni mean under the symmetric condition $p = q = 1$:

$$BM_i = \left(\frac{1}{n(n-1)} \sum_{\substack{j=1 \\ j \neq t}}^{n} \sum_{t=1}^{n} y_{ij}\ y_{it} \right)^{\frac{1}{2}}$$

where:

- BM_i is the integrated performance score of alternative i,
- y_{ij} and y_{it} represent the weighted normalized scores of criteria $j$and t,
- the interaction between all distinct pairs of criteria is explicitly considered.

The alternatives were ranked in descending order according to their BM_ivalues. A higher BM_iindicates superior overall performance considering both criterion importance and inter-criterion interactions.

Results

This study evaluated the suitability of six dairy cattle breeds for the Western Mediterranean Region using a picture fuzzy–based multi-criteria decision-making framework incorporating criterion interactions through a Bonferroni aggregation mechanism. Individual evaluations provided by five equally weighted decision makers were aggregated into a group picture fuzzy decision matrix, and final rankings were obtained using a score-based PFIBM/Bonferroni approach.

After transforming picture fuzzy evaluations into crisp scores and applying the Bonferroni-based interaction aggregation ($p = q = 1$), the integrated performance scores of the alternatives were calculated. The resulting ranking of dairy cattle breeds is as follows: Jersey, Anatolian Black, Simmental, Brown Swiss, Montbéliarde, and Holstein.

The results indicate that Jersey is the most suitable breed for the Western Mediterranean region. This outcome is mainly attributed to its strong performance in milk fat and protein content, feed conversion efficiency, heat tolerance, and reproductive efficiency. The Anatolian Black breed ranks second despite its relatively low milk yield, reflecting its exceptional adaptability to local environmental conditions, high disease resistance, and strong resilience to heat stress. Simmental occupies the third position due to its balanced performance across productivity- and adaptability-related criteria. Brown Swiss and Montbéliarde demonstrate moderate performance across most criteria, while Holstein ranks last because its high milk production potential is offset by weaknesses in heat tolerance and local adaptability, which are critical under Mediterranean climatic conditions.

To assess the stability and reliability of the proposed decision-making framework, a robustness analysis was conducted by systematically varying the weights of the most influential criteria, namely heat tolerance (C7) and local adaptability (C9). The weights of these criteria were independently and jointly modified within ±10% and ±20% intervals, while the remaining criteria weights were proportionally normalized to ensure that the total weight remained equal to one.

The analysis demonstrates that the ranking of alternatives remains unchanged under all moderate weight-variation scenarios. In all tested cases, the ranking order consistently remained Jersey, Anatolian Black, Simmental, Brown Swiss, Montbéliarde, and Holstein. This finding confirms that the proposed PFIBM/Bonferroni-based model is robust to reasonable uncertainty in criterion weights.

Ranking changes were observed only under extreme and unrealistic weighting scenarios, in which the weight assigned to local adaptability (C9) was substantially increased while the weight of heat tolerance (C7) was simultaneously reduced to very low levels. Under such conditions, the Anatolian Black breed marginally outperformed Jersey and ranked first. These results indicate that the dominance of Jersey is not sensitive to moderate variations in expert judgment and that a reversal of the ranking would require a deliberate and disproportionate emphasis on local adaptability alone.

Overall, the robustness analysis confirms that the proposed picture fuzzy interaction-based framework produces stable and reliable results under realistic decision-making uncertainty. The consistent ranking across multiple scenarios supports the applicability of the model as a dependable decision support tool for dairy cattle breed selection in regions exposed to climatic stress.

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CHAPTER 2

A FRAMEWORK TO EVALUATE THE BARRIERS OF AUTONOMOUS VEHICLES APPLICATIONS IN INDUSTRY 5.0 THROUGH MCDM

NİHAN ÇAĞLAYAN[1]

Introduction

Industry 5.0 requires human-machine collaboration with technological advances; however, it should be consisted with ethical, social, and environmental dimensions. This approach requires autonomous systems to consider not only their technical performance but also the human factor, ethical decision-making processes, and sustainability. Autonomous vehicles, in particular, play an important role in Industry 5.0's human-centered production vision, and multiple criteria must be balanced in the decision-making processes of these vehicles. The widespread use of autonomous vehicles in industrial applications requires overcoming numerous obstacles, such as safety, ethics, energy efficiency, human-machine interaction, and cybersecurity. These barriers are shaped not only by technological and human factors, but also by external factors such as public policies and regulatory frameworks. In this context, the integration of autonomous systems will lead to significant changes

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in both industrial processes and daily life. To manage these obstacles, MCDM (Multi-Criteria Decision Making) methods offer the opportunity to comprehensively evaluate the expectations of different stakeholders and multi-dimensional performance criteria. MCDM methods make decision-making processes more transparent and, at the same time, have the potential to increase the effectiveness of human-machine collaboration thanks to their ability to balance various criteria (Yilmaz and Ecemis Yilmaz, 2024). Therefore, the effective use of these methods is critical for the successful implementation of Industry 5.0.

Autonomous vehicles have emerged as a continuation of the automation and digitalization processes that began with Industry 4.0. Autonomous vehicles are preferred in wide range of application in states and private sectors (Ecemis Yilmaz, 2023). Industry 4.0 has revolutionized the manufacturing and service sectors with technologies such as cyber-physical systems, the Internet of Things (IoT), artificial intelligence (AI), and big data analytics. However, these technological advances have greatly affected the human factor, leading to unemployment in the labor market and negative consequences in the employee ecosystem. Autonomous vehicles have emerged as a continuation of the automation and digitization processes that began with Industry 4.0. AUIndustry 4.0 has revolutionized the manufacturing and service sectors with technologies such as cyber-physical systems, the Internet of Things (IoT), artificial intelligence (AI), and big data analytics. However, these technological advances have greatly affected the human factor, leading to unemployment in the labor market and negative consequences in the employee ecosystem (dos Santos Ramos Xavier et al., 2024a). Industry 5.0, on the other hand, focuses on human intellectual and cognitive abilities, aiming to use technology in a way that is compatible with humans and sustainable.

The role of autonomous vehicles in Industry 5.0 applications is considered not only as a technical innovation but also as a tool for social and economic transformation. Autonomous vehicles are particularly important in developing countries due to their potential to reduce traffic accidents caused by human error (dos Santos Ramos Xavier et al., 2024a). A study found that in countries with high rates of traffic accidents caused by human error, significant improvements in traffic safety are expected with the widespread adoption of autonomous vehicles. However, there are various obstacles to implementing this technology, including the inadequacy of obstacle detection technologies, users' perceptions of the technology, interaction problems between pedestrians and drivers, the cost competitiveness of vehicles, and road safety. These obstacles are not only technical but also involve social, economic, and cultural dimensions (dos Santos Ramos Xavier et al., 2024).

Another obstacle faced by autonomous vehicles in Industry 5.0 applications is the management of uncertainty and multiple criteria in decision-making processes. Naciri et al. (Güdek, 2023) note that decision-making processes become complex when they involve multi-criteria evaluation and uncertainty. The authors emphasize the importance of using MCDM methods in such complex decision-making processes, stating, "*The decision-making process becomes quite complex when it involves multi-criteria evaluation and uncertainty; this is the most common situation encountered in the industrial field." (Naciri et al., 2024)*. Additionally, it has been stated that MCDM methods provide a systematic framework for comparing different decision-making methods and selecting the most appropriate one.

The philosophy of Industry 5.0 aims to maximize the opportunities offered by technology while highlighting the creative contributions of people. This human-centered approach increases workforce participation, ensuring the best possible integration of both employees and technology. Furthermore, taking the human factor into account in this process enables complex problems to be solved more effectively through collaboration between various disciplines. As a result, it becomes possible to develop more flexible and adaptable systems in industrial environments. Industry 5.0 stands out as a new industrial paradigm that emphasizes human-centered approaches, sustainability, and human-machine collaboration. This transformation has increased the need to evaluate the role of autonomous vehicles in industrial applications and the obstacles they face using multi-criteria decision-making (MCDM) methods. Autonomous vehicles require advanced decision support systems and multidimensional evaluation approaches to respond to the human-machine interaction, ethical, safety, and flexibility requirements brought about by Industry 5.0. Therefore, MCDM methods play a critical role in managing the complex, multi-criteria decision-making processes that autonomous vehicles encounter in industrial environments. This study aims to prioritize the fundamental barriers to the widespread adoption of autonomous vehicles within the framework of the Industry 5.0 approach using the MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) method.

Literature

The human-centered, sustainable, and adaptable production vision of Industry 5.0 heavily relies on autonomous vehicles. Industry 5.0 is a transformation process that emphasizes human-machine collaboration, ethical responsibilities, sustainability, and social benefit, in contrast to Industry 4.0's automation and digitalization-focused paradigms. Studies in the literature demonstrate that although the widespread use of autonomous vehicles presents benefits like productivity, adaptability, and customization in manufacturing procedures, it also encounters a variety of challenges. An interdisciplinary analysis encompassing technological, ethical, human-machine interaction, environmental, economic, and legal aspects is necessary to enumerate these challenges. The human-centered, sustainable, and adaptable production vision of Industry 5.0 heavily relies on autonomous vehicles. Industry 5.0 is a transformation process that emphasizes human-machine collaboration, ethical responsibilities, sustainability, and social benefit, in contrast to Industry 4.0's automation and digitalization-focused paradigms. Studies in the literature show that although the widespread use of autonomous vehicles presents benefits like productivity, adaptability, and customization in manufacturing processes, it also encounters a number of challenges. An interdisciplinary examination of the technological, ethical, human-machine interaction, environmental, economic, and legal aspects is necessary to enumerate these challenges (Güdek, 2023).

Industry 5.0 is a transformation process that emphasizes human-machine collaboration, ethical responsibilities, sustainability, and social benefit, in contrast to Industry 4.0's automation and digitalization-focused paradigms. Studies in the literature show that although the widespread use of autonomous vehicles presents benefits like productivity, adaptability, and customization in manufacturing processes, it also encounters a number of challenges. An interdisciplinary examination of the technological, ethical, human-machine interaction, environmental, economic, and legal aspects is necessary to enumerate these challenges (Güdek, 2023). There are numerous obstacles to the widespread adoption of these technologies in production environments (Kirişçi & Şimşek, 2023). Additionally, it is crucial to overcome the operational and technical obstacles that arise when integrating autonomous vehicles into industrial applications. These challenges can occasionally be caused by inadequate infrastructure or by users' difficulties adjusting to new technologies. Consequently, the application of MCDM techniques improves both technological efficiency and the caliber of human-machine cooperation (Hamad et al., 2025). Because improved decision-making processes allow for more efficient resource use and lessen environmental effects, this strategy also helps achieve sustainability goals (Fourastier et al., 2020).

In addition to technological advancements, Industry 5.0 is shaped by a human-centered approach that promotes worker participation and human creativity, allowing for deeper and more significant interaction in production processes. It is crucial to create particular decision-making procedures to guarantee user safety and respect moral principles in order for autonomous vehicles to operate efficiently. For instance, putting user experience and human safety first when operating autonomous systems requires the application of MCDM techniques. By facilitating the methodical assessment of various decision options and criteria, MCDM makes it possible to use autonomous vehicles more effectively and efficiently (Claussmann et al., 2018).

The primary challenges that autonomous vehicles face when making decisions are data uncertainty, which leads to technical difficulties; conflicting performance standards; cybersecurity risks; moral quandaries; and the intricacy of human-machine interaction. In the technical domain, data uncertainty results from incomplete, erroneous, or deceptive data that autonomous systems need to make the right decisions. Simultaneously, systems struggle to decide which parameters to prioritize due to conflicting and multiple performance criteria. Another challenge in the technical domain is cybersecurity threats, which can jeopardize autonomous vehicles' interactions with their environment and thus undermine their dependability. Additionally, ethical conundrums make it challenging for autonomous systems to make the best choices in certain circumstances, which complicates human-machine interaction and increases uncertainty. Therefore, taking these factors into account is essential for autonomous cars to engage in the Industry 5.0 ecosystem in an efficient and moral manner.

Technological Obstacles The suitability of the technology infrastructure and integration issues are two major obstacles to the broad use of autonomous vehicles in Industry 5.0 applications. For autonomous cars to operate efficiently, technologies like digital twins, the Internet of Things, artificial intelligence, and big data are essential (Stogia et al., 2025). But these technologies' scalability, interoperability, energy efficiency, and cybersecurity continue to be major obstacles. Specifically, while real-time data integration and predictive analytics are expected to optimize production processes through digital twins, it is difficult to develop and implement these systems in a way that is compatible with heterogeneous production technologies (Asranov et al., 2024). In the context of Industry 5.0, digital twins must also be integrated with human-centered design principles. Currently, new approaches are required to incorporate the human element into procedures (Biondani et al., 2025).

Cybersecurity is another technological barrier to the widespread use of autonomous vehicles. By facilitating the sustainable delivery of customized goods and services, Industry 5.0 represents a new stage in the digital transformation process. However, the cybersecurity risks that emerge during this process pose serious risks to businesses. Effective cybersecurity provision is closely linked to the policies these nations adopt, particularly in newly industrialized nations. For these nations, organizational measures are the most important cybersecurity indicator. Data security, network integrity, and operational security are all at risk as autonomous vehicles proliferate on production lines (Duran, 2024)

According to Claussmann et al. (Claussmann et al., 2018) the multi-criteria decision-making processes of autonomous vehicles must optimize factors like safety, legal requirements, passenger comfort, and energy consumption. This study proposes an MCDM framework for assessing uncertain sensor data that combines fuzzy logic and Dempster-Shafer theory. In the risk assessment and decision-making processes of autonomous vehicles, this method guarantees the thorough management of various criteria and uncertainty. "This study presents a new framework for multi-criteria decision-making," the authors write. The suggested method emphasizes the significance of MCDM in autonomous vehicle decision-making processes by using Dempster-Shafer theory to assess uncertain sensor data and fuzzy logic theory to handle heterogeneous criteria.

Ensuring safety and security in decision-making processes is another challenge for autonomous vehicles in Industry 5.0 applications. According to Fourastier et al. (Fourastier et al., 2020) autonomous intelligent systems' ability to make local decisions based on gathering environmental data determines their safety and security. Particularly in cyber-physical systems involved in safety-critical activities, the validity and scope of the decision function should be evaluated in light of underlying assumptions, uncertainty, and safety constraints. The authors emphasize that "the safety and security of autonomous intelligent systems depend on their local decision-making capabilities based on collected environmental information." This highlights that security and safety are crucial concerns that must be considered when making decisions, particularly for cyber-physical systems involved in safety-critical tasks. It is claimed that MCDM techniques offer a useful instrument for assessing security and safety standards in addition to other performance standards.

Another significant technical challenge faced by autonomous vehicles in Industry 5.0 applications is cybersecurity threats. Hamad et al. (Hamad et al., 2025) point out that as autonomous systems become more autonomous, cybersecurity risks also rise, and these risks need to be addressed at all architectural levels. In particular, sophisticated cybersecurity measures must be put in place at every level, from the physical layer to the inter-system layer, in order for autonomous vehicles to function safely and securely. "As autonomy increases, the risk of cybersecurity threats increases proportionally, requiring the development of advanced methods across all architectural layers of autonomous systems," the authors write, emphasizing that cybersecurity is a fundamental challenge for autonomous vehicles. As a result, MCDM techniques are crucial to the thorough evaluation of cybersecurity risks in conjunction with other factors.

Another significant obstacle for autonomous vehicles in Industry 5.0 applications is the complexity of human-machine cooperation. Even though Industry 5.0 emphasizes human-machine collaboration and human-centered approaches, the human element must be taken into account in autonomous vehicle decision-making processes. According to Stogia et al. (Stogia et al., 2025) Industry 5.0 places a strong emphasis on ethical AI, sustainability, and human-machine cooperation. The authors stress that "Industry 5.0 represents a significant transformation in industrial ecosystems that prioritize human-machine collaboration, sustainability, and ethical artificial intelligence," emphasizing that human-machine collaboration is an essential component that autonomous systems' decision-making processes must take into account. As a result, MCDM techniques guarantee that ethical standards and the human element are thoroughly considered during the decision-making process.

The significance of human-robot interaction and human-machine collaboration concepts should be highlighted when analyzing the challenges of autonomous vehicles in Industry 5.0 applications. Industry 5.0 deals with human-machine cooperation in a framework that combines the accuracy and efficiency of machines with human creativity and intuition (Pawar et al., 2025). In this regard, human-robot interaction should be taken into consideration when designing user interfaces for autonomous vehicles. According to Amanatidis et al. (Amanatidis et al., 2018) user interfaces for autonomous vehicles should vary based on the degree of automation, and they should get smarter and more autonomous as the level of automation rises. This method signifies a change from conventional "master-slave" interaction to "equal-level" interaction, in which robots and humans work together on an equal basis.

Ergonomic Barriers and Human-Machine Interaction Industry 5.0 is centered on human-machine cooperation. The inability to create safe, effective, and ergonomic human-machine interaction is one of the main obstacles to the widespread adoption of autonomous vehicles. Industry 5.0 addresses this shortcoming by providing a human-centered paradigm, as discussed in the literature, whereas Industry 4.0's automation-focused approach resulted in the exclusion of human labor from production environments (Teoman, 2024). However, there are still issues with ergonomics, usability, and accessibility that must be resolved when integrating human-machine collaboration into production processes (Palazhchenko et al., 2024). In particular, issues such as perception, trust, explainability, and ethical responsibilities come to the fore in human-robot interaction (Demircioğlu & Canbay, 2021). One major barrier to social acceptance is how moral and ethical obligations will be upheld in intelligent autonomous systems' decision-making processes (Demircioğlu & Canbay, 2021).

In the context of Industry 5.0 applications, there are numerous moral and legal obstacles to the widespread use of autonomous vehicles. To understand these challenges, one must consider not only technological advancements but also social, legal, and ethical norms. In the process of integrating autonomous vehicles into society, concerns like safety, responsibility sharing, legal regulations, and ethical decision-making processes are closely related to the human-centered and collaborative vision of Industry 5.0. According to Wang et al.'s study, autonomous vehicles' ethical decision-making processes are primarily caused by the challenges of translating existing ethical theories into practical applications. Despite decades of research in the field of machine ethics, the study claims that ethical decision-making processes in autonomous driving present more complex and distinct challenges. Additionally, it is said that researchers, legislators, and the automotive sector continue to work together to find a consistent and all-encompassing solution in this field (Wang et al., 2022). The human-centered and ethics-based technological transformation that Industry 5.0 envisions is directly related to this situation because giving machines the authority to make moral decisions presents a significant barrier to social acceptance and trust.

A major barrier to Industry 5.0's goal of improving human-machine interaction is the social acceptance of autonomous vehicles' moral behavior and its incorporation into the legal framework. Evans et al. (Evans et al., 2020) developed the "Ethical Valence Theory" to evaluate whether ethical choices made by autonomous cars are socially acceptable. This theory holds that when a vehicle makes decisions about its environment, it tries to lessen the moral demands that various road users place on it. The goal of ethical practice is to be consistent with reality by quantitatively evaluating the harm caused by decisions and the uncertainties associated with them. This approach offers a flexible calculation method that permits the evaluation of various moral positions and social expectations, rather than providing a definitive solution for how ethical theories should be reflected in vehicle behavior. Although this flexibility aligns with the diversity and inclusivity ideals of Industry 5.0, a major barrier to standardization and regulation is the diversity of ethical choices based on social and cultural context.

Another major challenge in Industry 5.0 applications is the legal status and liability sharing of autonomous vehicles. The study by Ilkova and Ilka's (Ilkova & Ilka, 2017) highlights the necessity of amending current traffic laws to permit the use of autonomous vehicles on public roads by comparing the legal regulations of autonomous vehicles in Europe and the US. Additionally, it was mentioned that legal regulations present serious difficulties for insurance companies, automakers, drivers, and consumers. To put it another way, in order to discuss the applicability of various legal provisions, technical professionals must also be aware of legal regulations. The integration of technical and legal fields is necessary for the interdisciplinary collaboration and holistic approach that Industry 5.0 envisions, but the current legal framework is not flexible enough to facilitate this integration, which presents a major challenge.

Regulatory and legal obstacles the absence of legal and regulatory frameworks is another major obstacle to the widespread use of autonomous vehicles in Industry 5.0 applications. New laws pertaining to data security, personal data protection, liability sharing, and occupational health and safety are necessary due to the extensive use of autonomous systems in production processes (Aksoy et al., 2024). To guarantee human safety in production settings, specific legal requirements must be set for the development and application of AI-supported systems. The approach of Industry 5.0, which places a high priority on worker health and human safety, calls for the creation of new regulations and the updating of current legal frameworks (Aksoy et al., 2024).

Organizational and financial obstacles Economic and organizational factors are another obstacle to the widespread use of autonomous vehicles in Industry 5.0 applications. For small and medium-sized businesses, the technological infrastructure investments mandated by Industry 5.0 represent a substantial cost factor (Dossou & Nshokano, 2024). SMEs encounter financial, technical, and human resource obstacles to this transition, whereas large corporations can more readily integrate digital twins and autonomous systems (Dossou & Nshokano, 2024). Furthermore, current organizational structures and business models must be redesigned in accordance with the core tenets of Industry 5.0, such as sustainability and human-centeredness (Güdek, 2023). During this transformation process, businesses must adapt to strategic and technological requirements, develop new skill sets, and ensure that employees adapt to the transformation (Pinzone et al., 2024).

The effectiveness of human resources in digital transformation processes is another organizational barrier to the widespread adoption of autonomous vehicles. Industry 5.0 suggests giving workers' and society's needs and welfare top priority (Teoman, 2024). Beyond financial considerations, though, the creation, design, and adaptation of new technologies necessitate improving workers' competencies and giving them new skills (Pinzone et al., 2024).

One of the main factors directly influencing the widespread adoption of autonomous vehicles in Industry 5.0 applications is economic barriers. Raj et al. (Raj et al., 2020) discovered that a lack of consumer acceptance is the biggest barrier to the adoption of autonomous vehicles in their study that used a multi-criteria decision-making approach. More tangible organizational and economic obstacles, like the absence of industry standards and insufficient regulatory frameworks, must be addressed in order to get past this obstacle. To put it another way, high investment costs economically restrict the technology's commercialization and widespread adoption, while organizational standards and regulations hinder the sector's ability to undergo a thorough transformation.

Industry 5.0 is a new paradigm that emphasizes technological innovation, sustainability, and a human-centered approach in industrial transformation. This includes changes in organizational and economic processes in addition to technological advancements. In the context of Industry 5.0, the spread of sophisticated automation applications like driverless cars necessitates a more intricate and multifaceted approach to overcoming organizational and financial obstacles. In this regard, it is crucial from an academic and industrial standpoint to investigate the organizational and financial obstacles of autonomous vehicles in Industry 5.0 applications from an interdisciplinary standpoint. Increasing operational effectiveness and employee satisfaction through improved human-machine collaboration is one of Industry 5.0's core objectives. However, in order to accomplish these objectives, organizational and financial obstacles must be removed in addition to technological advancements. Adoption of high-tech applications, like self-driving cars, in industrial settings necessitates not only technical proficiency but also organizational flexibility and economic viability. Currently, Industry 5.0's human-centered approach aims to create new organizational structures and business models while balancing the social and economic effects of technological advancements. Yaqot et al. (Yaqot et al., 2024) emphasizes that in order to maximize human-machine collaboration in Industry 5.0, workforce competencies must be developed and digital governance issues must be resolved. Along with organizational challenges like workforce loss, skill gaps, and ethical dilemmas, economic sustainability stands out as a major barrier in this context. One of the most notable applications of Industry 5.0 is autonomous vehicles. The extensive use of autonomous vehicle technology has several benefits, including lowering transportation-related accidents brought on by human error, boosting productivity, and guaranteeing sustainability (dos Santos Ramos Xavier et al., 2024b).

One of the main factors directly influencing the widespread adoption of autonomous vehicles in Industry 5.0 applications is economic barriers. A lack of consumer acceptance is the biggest barrier to the adoption of autonomous vehicles, according to a study by Alok Raj et al. (Raj et al., 2020) that used a multi-criteria decision-making approach. More tangible organizational and economic obstacles, like the absence of industry standards and insufficient regulatory frameworks, must be addressed in order to get past this obstacle. To put it another way, high investment costs economically restrict the technology's commercialization and widespread adoption, while organizational standards and regulations hinder the sector's ability to undergo a thorough transformation.

Organizational obstacles in digital transformation processes are another significant factor impacting the spread of autonomous vehicles in Industry 5.0 applications. When integrating digital technologies, factors like organizational culture, leadership style, and employee motivation are crucial, especially in large-scale industrial enterprises. According to Syversen et al., the company's leadership style and strategic orientation have a direct impact on employee skill development and motivation during the shift from Operator 4.0 to Operator 5.0. The failure of technological applications can be caused by leaders who do not adequately support change or by an organizational culture that is closed off to innovation. Similar circumstances also occur when autonomous vehicles are incorporated into manufacturing and transportation procedures.

One of the most significant multidisciplinary research areas in the context of autonomous vehicles and Industry 5.0 applications today is sustainability and environmental challenges. As industrial revolutions have progressed, industrial applications have shifted from an emphasis on efficiency and automation to a new paradigm known as Industry 5.0, which is based on sustainability, people, and the environment.

Industry 5.0 presents a paradigm centered on sustainability and environmental awareness (Güdek, 2023). While the proliferation of autonomous vehicles offers new opportunities in terms of energy efficiency, resource utilization, and environmental impact, it also faces various obstacles in achieving sustainability goals. In particular, issues such as the energy consumption of digital twin and IoT-based systems, the carbon footprint of data centers, and electronic waste management are important obstacles that must be considered in sustainable Industry 5.0 applications (Stogia et al., 2025). Furthermore, the widespread use of autonomous vehicles in production processes must be designed in line with green production and circular economy principles (Güdek, 2023).

In the context of sustainability, urban logistics and last-mile delivery procedures represent another significant application area for autonomous vehicles. In response to rising delivery demands, especially during the COVID-19 pandemic, the integration of electric and autonomous vehicles into logistics networks has gained prominence. In addition to lowering emissions, electric and driverless cars improve delivery effectiveness and bolster the robustness of logistics networks. Electric car fleets and autonomous delivery robots lower labor costs, ease traffic, and lessen carbon emissions. However, inadequate charging infrastructure, range restrictions, and technological maturity are the main barriers to these technologies' widespread adoption. Overcoming these challenges is essential for effective and sustainable urban logistics (Alsaleh & Alsaleh, 2025).

Sustainability in Industry 5.0 applications is not just about lessening environmental effects; it also strives for social and economic change by implementing circular economy concepts. Industry 5.0 accelerates economic transformation in areas like green jobs, eco-innovation, and green patents by integrating with circular economy activities, according to research done in the European

Union. Through technological innovation, this integration promotes economic growth and makes it easier to apply sustainable development principles in a variety of sectors (Sulich, 2024).

Using MCDM techniques to manage the challenges autonomous vehicles face in Industry 5.0 applications guarantees that ethical, social, and environmental factors are taken into consideration in addition to technical performance requirements. In order to create moral decision-making procedures in ERP systems, Wankhade et al. compare fuzzy MCDM and OWA operators. "Fuzzy MCDM techniques allow for the consideration of multiple criteria and stakeholder perspectives, while OWA operators provide a robust framework for gathering uncertain and imprecise information," the authors say, highlighting the importance of MCDM in ethical decision-making processes (Wankhade et al., 2025). This method makes sure that when autonomous vehicles make decisions, social and ethical factors are taken into account in addition to technical ones.

In conclusion, the role of autonomous vehicles in Industry 5.0 applications necessitates striking a balance between a number of competing factors in a setting where ethics, sustainability, human-machine cooperation, and many other factors are important. Overcoming challenges calls for a comprehensive plan and an interdisciplinary approach. To achieve the human-centered, sustainable, and flexible production vision of Industry 5.0, a thorough examination of each challenge is essential. In this regard, MCDM techniques guarantee the comprehensive management of multifaceted challenges that autonomous vehicles encounter, including safety, cybersecurity, ethics, energy efficiency, and human-machine interaction. MCDM techniques must be successfully applied in decision-making processes in order to successfully integrate autonomous vehicles in Industry 5.0 applications.

MACBETH Method

The MACBETH method was created to provide a quantitative approach to decision-making based on the qualitative assessments of decision-makers. How to create a scale that would enable decision makers to express their degree of preference between options without requiring them to express their preferences in numerical form was the question on the minds of the researchers who created the method. As a result, the MACBETH method which relies only on semantic judgments like "weak" and "strong" in pairwise comparisons was developed. Pairwise comparisons based on the qualitative values of the criteria can also be used in this method to determine the relative weights of the criteria (Bana E Costa et al., 2012).

Pairwise comparisons based on the qualitative values of the criteria can also be used in this method to determine the relative weights of the criteria. The MACBETH method employs an interval scale, but it is comparable to MCDM techniques like AHP that rely on pairwise comparison results. Additionally, the MACBETH approach is different from other AHP techniques in that it bases comparisons on qualitative rather than quantitative values. Only semantic judgments like "weak" and "strong" are employed in pairwise comparisons using this method.

Step 1: A decision problem is defined.

$$C = \{c_1, c_2, \dots, c_n\}\ set\ of\ criteria$$

The objective is to determine the relative importance weights of the criteria.

$$w = (w_1, w_2, \dots, w_n)\ \ if\ w_i \geq 0, \sum_{i=1}^{n} w_i = 1$$

Step 2: Defining reference levels of criteria.

$$v(c_i^{worst}) = 0, v(c_i^{best}) = 100$$

Step 3: The difference in attractiveness between the pairs of criteria is qualitatively expressed by the decision maker. As shown in Table 1, the decision-maker uses one of the semantic categories to convey this difference.

$$\Delta_{ij} = v(c_i) - v(c_j)$$

$$\Delta_{ij} = \{0,1,2,3,4,5,6\}$$

Table 1 Semantic Categories

Semantic Categories	**Scale**
No	0
Very strong	1
Weak	2
Moderate	3
Strong	4
Very strong	5
Extreme	6

Step 4: Consistency constraint

$$\boldsymbol{v(c_i) - v(c_j) \geq \delta_{ij}}$$

where δ_{ij} is the minimum difference in attractiveness specified by the decision maker.

Step 5: Transitivity constraint

$$\begin{aligned}
&if\ v(c_i) - v(c_j) \geq \delta_{ij} \\
&and\ v(c_j) - v(c_k) \geq \delta_{jk} \\
&then\ v(c_i) - v(c_k) \geq \delta_{ij} + \delta_{jk}
\end{aligned}$$

Step 6: Creating the Linear Programming Model

$v(c_1), v(c_2), \ldots, v(c_n)$ where the decision parameters

$max \sum_{i=1}^{n} v(c_i)$	The objective function
$v(c_{worst}) = 0$	Pairvise comparison constraint
$v(c_{best}) = 100$	
$v(c_i) \geq v(c_j) \ \ if \ c_i \geq c_j$	Ranking constraint
$v(c_i) \geq 0$	Non-positivity restriction

Step 7: Calculation of the criteria weights and ranking of the criteria are as follows.

$$w_i = \frac{v(c_i)}{\sum_{k=1}^{n} v(c_k)}$$

$$c_i > c_j \leftrightarrow w_i > w_j$$

Numerical analysis

This study uses the MACBETH method to prioritize the basic obstacles to the widespread adoption of autonomous vehicles within the Industry 5.0 approach. In keeping with Industry 5.0's human-centered, sustainable, and resilient production philosophy, the assessment has taken into account ethical, social, environmental, and legal factors in addition to technological ones.

Table 2 lists the study's evaluation criteria, which include technological barriers, ergonomics and human-machine interaction, ethical and social barriers, organizational and economic barriers, legal and regulatory barriers, sustainability, and environmental barriers.

Table 2 The list of criteria

Criteria	Description
C1	Technological barriers
C2	Legal and regulatory barriers
C3	Economic and organizational barriers
C4	Human–machine interaction and ergonomics
C5	Ethical and social barriers
C6	Sustainability and environmental barriers

The pairwise comparison according to the semantic categories is demonstrated in Table 3.

Table 3 Attractiveness between the pairs of criteria

	C1	C2	C3	C4	C5	C6
C1	0	4	5	3	4	4
C2		0	3	2	3	2
C3			0	2	3	3
C4				0	2	3
C5					0	2
C6						0

The normalized criterion weights obtained because of the MACBETH linear programming solution are listed in Table 4 below.

Table 4 Weights of criteria

	Weight
C1	0.24
C5	0.20
C4	0.18
C2	0.15
C3	0.13
C6	0.10

Conclusion

There are multidimensional barriers to the widespread adoption of autonomous vehicles in Industry 5.0 applications. Overcoming these barriers requires comprehensive approaches based on technical, social, ethical, legal, and security considerations. In order to realize Industry 5.0's human-centered and sustainable production vision, autonomous vehicle technologies must be designed and implemented in a way that overcomes these barriers. The results of the multi-criteria decision analysis conducted using the MACBETH method in this study reveal the technological barriers to the widespread adoption of autonomous vehicles within the scope of Industry 5.0, legal and regulatory barriers, economic and organizational barriers, human-machine interaction and ergonomics, ethical and social barriers, and sustainability and environmental barriers. Especially in decision problems where uncertainty, subjective evaluation, and qualitative judgments prevail, such as human-centered production systems, the MACBETH method enables the transformation of qualitative expert opinions into a systematic, consistent, and mathematically expressible structure.

The recommended method, based on the analysis results, indicates that technological barriers have the highest priority, suggesting that autonomous vehicle systems have not yet fully achieved the flexibility, reliability, interoperability, and cyber-physical integration capabilities required by Industry 5.0. The legal and regulatory barriers in second place clearly reflect the time lag between technological developments and regulatory frameworks. The fact that economic and organizational barriers rank third highlights that autonomous vehicle investments are not only a technological process but also one that requires strategic and organizational transformation. The human-machine interaction and ergonomics criterion, ranked fourth, has been considered a secondary obstacle by decision-makers compared to technological and legal factors, despite the human-centered production approach that is the fundamental philosophy of Industry 5.0. The relatively lower priority given to ethical and social barriers indicates that, in the short term, businesses prioritize operational and regulatory risks over long-term social impacts. Sustainability and environmental barriers, which rank last, show that despite the environmental dimension of Industry 5.0 vision, they are still perceived as an indirect and secondary benefit area in autonomous vehicle applications. This finding reveals that environmental gains are often assumed to be a natural outcome of technological developments but are not sufficiently internalized as an independent priority criterion in decision-making processes.

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“Please review the following academic text from both a language and a technical aspect.

Language: Check grammar, punctuation, clarity, coherence, and formal academic tone.

Technical Accuracy: Evaluate whether the concepts, terminology, and methodology related to Multi-Criteria Decision Making (MCDM), Fuzzy Sets, and Fuzzy Logic are used correctly and appropriately. Assess the logical flow, problem framing, and suitability of the techniques within these subfields of industrial engineering.

If needed, suggest improvements in wording or technical precision without changing the intended meaning. If any parts are vague or methodologically weak, rewrite them.”

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CHAPTER 3

THE IMPACT OF THE METAVERSE ON INDUSTRY 4.0

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Introduction

The term Metaverse was first used in Neal Stephenson's 1992 novel Snow Crash. Today, the Metaverse is defined as a decentralized, persistent, and immersive three-dimensional online environment where the physical and virtual worlds seamlessly merge, allowing users to interact socially and economically through avatars. The Metaverse leverages emerging technologies such as extended reality (XR) (Augmented Reality/AR, Virtual Reality/VR, and Mixed Reality/MR), artificial intelligence (AI), blockchain, and IoT.

Industry 4.0 refers to the fourth industrial revolution, which aims to fundamentally transform traditional manufacturing using technology. This transformation focuses on the accelerated digitalization of manufacturing models. The key enablers of Industry 4.0 include technologies such as Cyber-Physical Systems (CPS), the Internet of Things (IoT), Big Data, and Artificial Intelligence (AI). The goals of Industry 4.0 include faster product development,

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fulfilling personalized demands (mass customization), flexible production, and resource efficiency.

The concept of the Industrial Metaverse has emerged as the next stage in this technological evolution. The Metaverse is an immersive, multi-user digital environment that combines the physical and virtual worlds, using technologies such as virtual reality (VR), augmented reality (AR), artificial intelligence, and blockchain.

The Industrial Metaverse is a subset of the Metaverse concept within an industrial context. It is a Metaverse sector that reflects and simulates machines, factories, cities, or transportation networks, offering participants fully immersive, real-time, interactive, persistent, and synchronous representations and simulations of the real world. The Industrial Metaverse is often seen as an integrated system that emphasizes real-time interactions in the visualization layer of CPS and acts as a digital twin of a manufacturing workspace. The Metaverse is generally considered to be a superset of the Digital Twin or one of the technologies enabling the Metaverse of the DT.

The Industrial Metaverse can be defined as a comprehensive and interconnected Digital Twin system that goes beyond being merely a digital copy of production facilities or equipment, reflecting the entire real-world industrial system into the virtual environment with a two-way flow. The application of the Metaverse to industrial environments is expected to provide significant benefits in areas such as remote operation and maintenance, training, design, and simulation. The Industrial Metaverse can completely transform how businesses evaluate past performance and strategically and operationally predict future outcomes.

Despite the immense potential offered by the Metaverse for Industry 4.0 and beyond applications, there are several significant barriers to the full adoption of this new paradigm. These challenges manifest themselves in technical, organizational, social, and regulatory dimensions.

Consequently, the integration of the Metaverse and Industry 4.0 represents a new phase of digital transformation in the manufacturing sector, and multi-criteria decision-making methods play a critical role in this transformation. Digital twins, IoT, cyber-physical systems, augmented and virtual reality technologies, big data analytics, and artificial intelligence applications enable the development of smarter, more flexible, and human-centered solutions in production processes. The use of MCDM methods is becoming increasingly important for managing the complex decision processes encountered in the integration of these technologies. In this context, the role of MCDM approaches in the integration of the Metaverse and Industry 4.0 stands out as one of the fundamental elements shaping the future of the manufacturing sector. This book chapter aims to systematically examine the fundamental challenges that hinder the integration of the Industrial Metaverse into Industry 4.0 environments. To this end, critical barriers such as infrastructure, systematic, technological, investment cost, cybersecurity, lack of competence, standardization, and legal uncertainty will be analyzed in detail.

Literature

The emergence of Industry 4.0 has brought digitalization and automation to the forefront of production processes. With this transformation, technologies such as cyber-physical systems, the Internet of Things (IoT), cloud computing, big data analytics, and artificial intelligence have become fundamental components of production environments. In recent years, the concept of the Metaverse has added a new dimension to this digitalization process, offering an interactive and immersive production ecosystem where the physical and virtual worlds converge. In this context, multi-criteria decision-making (MCDM) methods play a critical role in managing the complex decision-making processes that arise in the integration of Industry 4.0 and the Metaverse (Awotunde et al., 2024; Cali et al., 2022; Deveci et al., 2022; Huang et al., 2022; Lidong & Guanghui, 2016; Nugroho & Maulana, 2022; Yilmaz and Ecemis Yilmaz, 2024).

The Metaverse is defined as an environment supported by virtual and augmented reality technologies, where users interact through digital twins, cyber-physical systems, and IoT devices, enabling real-time data flow and collaboration (Ecemis Yilmaz, 2024). Digital twins, cyber-physical systems, and IoT, which are fundamental components of Industry 4.0, play a key role in the integration of the Metaverse into the manufacturing sector. Digital twins, as dynamic representations of physical objects or processes in a virtual environment, enable real-time data collection, analysis, and simulation. This makes applications such as monitoring, optimizing, and predictive maintenance of production processes possible (Intizar Ali et al., 2021). With the convergence of these technologies, it is possible to develop smarter, more flexible, and human-centered solutions in production environments (Yao et al., 2024). Digital twins provide a powerful tool for simulating, monitoring, and optimizing production processes by creating virtual representations of physical assets (Preuveneers et al., 2018). In particular, feeding digital twins with real-time data enables instant decision-making in production processes and allows for continuous process improvement (Kılıç et al., 2024). In this context, digital twins are seen to play a central role in the integration of Industry 4.0 and the Metaverse.

The integration of the Metaverse into the manufacturing sector brings not only technological transformation but also organizational and human-centered transformation. Particularly in the Industry 4.0 vision, where human-machine collaboration comes to the fore, Metaverse technologies are presented as a platform that enhances the human factor in production processes and offers more interactive and intuitive interfaces (Egbengwu et al., 2025). Augmented reality (AR) and virtual reality (VR) technologies are widely used in training employees in production processes, in maintenance and repair activities, and in remote monitoring and control applications (Da Silva Ribeiro Castro et al., 2023). These technologies enable users to interact with digital twins, visualize production processes in three dimensions, and analyze complex data in a more understandable way (Geng et al., 2022).

IoT, one of the fundamental components of Industry 4.0, is a key technology that enhances the applicability of the Metaverse in production environments. IoT devices and sensors continuously collect data from the physical environment, enabling this data to be transferred to the virtual environment through digital twins and cyber-physical systems. This makes real-time monitoring, control, and optimization possible in production processes (Souza et al., 2019). IoT-based digital twins enable adaptive, efficient, and sustainable operations in production processes (Stogie et al., 2025).

Additionally, the data flow provided by IoT, combined with big data analytics and artificial intelligence applications, enables more accurate and faster results in decision-making processes (Kaur & Kaur, 2016). The complex decision-making processes arising from the integration of the Metaverse and Industry 4.0 require the evaluation of numerous criteria and alternatives. At this point, multi-criteria decision-making (MCDM) methods come into play. MCDM methods enable the systematic analysis of multi-dimensional and multi-criteria problems encountered in production processes and facilitate the making of the most appropriate decisions. Particularly in Industry 4.0 and Metaverse integration, the use of MCDM methods is increasingly prevalent in areas such as technological infrastructure selection, investment decisions, process optimization, and performance evaluation (Patel & Vinodh, 2024). In a study, key technologies enabling additive manufacturing and Industry 4.0 integration in small and medium-sized enterprises (SMEs) were identified and evaluated in order of importance using the MCDM method. As a result, IoT, cloud computing, and cyber-physical systems emerged as the most important Technologies (Intizar Ali et al., 2021). This finding demonstrates that multi-criteria decision-making approaches play a critical role in the integration of the Metaverse and Industry 4.0 as well.

In assessing the applicability of digital twins in supply chain management, multi-criteria decision analysis (MCDA) methods are used to enable businesses to make strategic decisions based on criteria such as interoperability, integration challenges, and operational efficiency (Neto et al., 2025). MCDA methods such as PROMETHEE II enable the systematic evaluation of the challenges and opportunities encountered in the integration of digital twins into the supply chain (Neto et al., 2025).

The implementation of the metaverse in the manufacturing sector requires not only the integration of technological infrastructures but also the redefinition of human-machine interaction. In particular, augmented reality and virtual reality technologies facilitate workers' access to information in production processes and provide interactive and immersive experiences in training and maintenance processes (Ramalho et al., 2024). These technologies increase flexibility and resilience in production environments, enabling faster and more effective solutions to be developed in response to unexpected situations (Ramalho et al., 2024). Additionally, augmented reality-based decision support systems enable the three-dimensional visualization of simulation results in production processes, helping decision-makers better understand how the system operates (Karlsson et al., 2017). Such applications are examples of the innovative approaches that the Metaverse brings to decision-making processes in the manufacturing sector.

In digital twins and Metaverse integration, ensuring two-way data flow and control between real and virtual environments is of great importance. This allows changes occurring in physical systems to be instantly reflected in the virtual environment, and optimizations or simulations performed in the virtual environment to be applied to the physical system (Kılıç et al., 2024). This two-way integration provides flexibility, speed, and accuracy in production processes. Furthermore, the combination of digital twins with augmented reality and virtual reality technologies enables the development of more intuitive and interactive interfaces in production processes (Geng et al., 2022). Such applications demonstrate that the Metaverse plays a significant role in enhancing human-machine interaction and supporting decision-making processes in the manufacturing sector.

Big data analytics and artificial intelligence applications also play an important role in Industry 4.0 and Metaverse integration. Large amounts of data collected from production processes are analyzed using artificial intelligence and machine learning algorithms and used in areas such as process optimization, maintenance, and quality control (Razzaq et al., 2024). Specifically, in digital twin-based virtual reality models, machine learning and deep learning algorithms are used to predict the maintenance requirements of production machines in advance and minimize the risk of failure. Such applications highlight the importance of data-driven decision-making processes in Metaverse and Industry 4.0 integration.

The implementation of the metaverse in the manufacturing sector also requires the redesign of organizational structures and business processes. In particular, new approaches are being developed in areas such as collaboration, information sharing, and process management in virtual factory environments, and the most suitable strategies are being determined using multi-criteria decision-making methods in these processes (Stefko et al., 2025). For example, digital twin-based virtual factories and cyber-physical production systems support applications such as big data tracking in production processes, remote fault diagnosis, and predictive maintenance, thereby ensuring that production processes are more efficient and sustainable (Stefko et al., 2025). Additionally, in Metaverse-based business processes, three-dimensional simulation and visualization tools supported by augmented reality and virtual reality technologies help achieve more accurate and faster results in decision-making processes.

One of the most significant challenges encountered in Industry 4.0 and Metaverse integration is ensuring the interoperability of different technologies and systems. In particular, issues such as data security, scalability, and energy efficiency come to the fore in the integration of digital twins and IoT devices (Stogia et al., 2025) . To overcome these challenges, innovative solutions such as blockchain-based data management, edge computing, and artificial intelligence-supported decision-making systems are being developed (Stogie et al., 2025). Additionally, in the integration of the Metaverse and Industry 4.0, the human factor must be prioritized, and the ethical, social, and environmental dimensions of technological progress must be taken into account (Yao et al., 2024).

In this context, human-centered production approaches and sustainability-focused solutions will be decisive in shaping the production environments of the future.

The digitalization and automation brought about by Industry 4.0 has not been limited to production processes but has also led to significant transformations in areas such as the supply chain, logistics, maintenance, and education. For example, the concept of Logistics 4.0 refers to the integration of Industry 4.0 technologies into logistics processes. Thanks to this integration, features such as pattern recognition, self-organization, and agility come to the fore in logistics processes, and Multi-Criteria Decision Making (MCDM) methods can be used to determine which areas should be prioritized (Sir & Peker, 2025).

Similarly, in maintenance processes, the concepts of predictive maintenance and Maintenance 4.0 have emerged alongside Industry 4.0 technologies. In these processes, technologies such as artificial intelligence, IoT, and big data analytics have been used to increase the transparency and efficiency of maintenance processes (Alves et al., 2024). Another important aspect of decision-making processes in metaverse applications is ensuring ethical principles and reliability. Behera and colleagues' study states that ethical issues arising in the mutual relationships between businesses and users in the metaverse environment directly affect decision-making processes (Behera et al., 2024). The study indicates that four fundamental ethical principles business benefit assessment, fairness, explainability, and reliability play a critical role in managing complex relationships and improving decision-making processes in the metaverse environment (Behera et al., 2024).

Prioritizing the Barriers to Implementing the Metaverse in Industry 4.0

AHP Method

Managing uncertainty and risk in decision-making processes is another fundamental challenge faced by MCDM methods in metaverse applications. In particular, most classical MCDM methods do not sufficiently consider decision-makers' risk perception and psychological behavior.

This study aims to analyze the barriers to the implementation of the Metaverse in Industry 4.0 environments and to reveal the relative importance levels of these barriers. The literature shows that there are limited studies on the quantitative prioritization of this issue. Therefore, the AHP method is proposed to evaluate various infrastructure, systematic, technological, investment cost, cybersecurity, lack of competence, standardization, and legal uncertainty factors related to the Metaverse's Industry 4.0 adaptation process. Prioritizing the Barriers to Implementing the Metaverse in Industry 4.0

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The Analytic Hierarchy Process (AHP) stands out as one of the most widely used and effective tools among multi-criteria decision-making (MCDM) methods. In modern decision-making processes, particularly in solving complex and multi-dimensional problems, the systematic approach offered by AHP has gained widespread acceptance in both academic and applied fields. This method is based on transforming the complex problems faced by decision-makers into a hierarchical structure and determining the weights of criteria and alternatives through pairwise comparisons within this structure. The multidisciplinary application areas of AHP are closely related to the method's flexibility and its ability to systematically incorporate decision-makers' subjective judgments into the model (Sharma et al., 2022). The steps of the method are listed below.

Step1:Determining the criteria. List the criteria to prioritize.

Step2:Creating the pair comparison matrix. Categories are compared in pairs using Saaty's 1-9 scale. A pair comparison matrix between factors is created. a_{ij} is the pair comparison value between criterion i and criterion j, and the a_{ij} value is obtained from 1 - a_{ji}. Decision matrices are created using the 1-9 comparison scale proposed by Saaty below. Table 1 is shown below.

Table 1 Comparison scale

Importance	Definition	Explanation
1	Equal importance	Both options are considered slightly more important than the other.
2	Weak or slight	One criterion is considered slightly more important than the other.
3	Somewhat important	One criterion is considered much more important than the other.
4	Moderately important	The criterion is considered much more important than the other.
5	Very important	Various information indicates that one criterion is extremely important compared to the other.
6	Very important	Both options are equally important.
7	Extremely important	One criterion is considered slightly more important than the other.
8	Very strong	One criterion is considered much more important than the other.
9	Extremely important	The criterion is considered much more important than the other criteria.

Reference: (Wind & Saaty, 1980)

$$A = \begin{bmatrix} 1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} = {}^{1}/_{a_{1n}} & \cdots & 1 \end{bmatrix} \tag{1}$$

Step 3: Normalizing the matrix. Each column is normalized to dividing it by its own sum.

$$n_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{2}$$

Step 4: Calculation of criterion weights. The average of each row is taken. These values are the relative importance weights of the criteria.

$$w_i = \left(\frac{1}{n}\right)\sum_{i=1}^{n} n_{ij} \tag{3}$$

Step 5: Consistency analysis is calculated. The most important part of AHP is to check whether the decision maker is consistent.

Step 5.1: The weighted total vector is calculated.

Step 5.2: Maximum eigenvalue, λ_{max} is calculated.

$$\lambda_{max} = \left(\frac{1}{n}\right)\sum_{i=1}^{n} \frac{\sum_{j=1}^{n} a_{ij} w_i}{w_i} \tag{4}$$

Step 5.3: The Consistency Index, CI, is calculated.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{5}$$

$$CR = CI/RI \tag{6}$$

Table 2 Saaty's Random Index

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
R	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53	1.56	1.57	1.59

Reference: (Güner, 2003)

If CR defined by Eq.5 is less than 0.01, the comparison matrix is considered consistent.

Step 6: The criteria are ranked. Weight values are ranked from highest to lowest. The criterion with the highest weight is the most important criterion.

The Numerical Analysis

The digital transformation process brought about by Industry 4.0 has the potential to fundamentally change production, logistics, and business models. One of the technologies emerging within this transformation, the metaverse, increases efficiency, flexibility, and collaboration in production processes with its innovative components such as virtual reality, augmented reality, and digital twins. However, the widespread adoption of metaverse applications in the context of Industry 4.0 faces multidimensional and complex obstacles. (C1)Infrastructure and interoperability, (C2) cybersecurity and data management, (C3) human factors and skills, (C4) legal and regulatory uncertainty, (C5) economic and strategic risks, and (C6) sustainability and energy consumption are factors that may hinder the implementation of the metaverse in industrial applications. In this study, these obstacles highlighted in the literature are defined as criteria, and the relative priorities of these criteria in the context of Industry 4.0 will be determined using the AHP decision support method. Thus, it will be systematically revealed which factors require priority solutions in the integration of the metaverse into industry. Table 3 shows a comparison of the obstacles themselves.

Table 3Criteria List

Criteria	C1	C2	C3	C4	C5	C6
C1 Infrastructure & Interoperability	1	1/2	2	3	1/2	3
C2 Cybersecurity & Data Management	2	1	3	4	2	4
C3 Human Factors & Skills	1/2	1/3	1	2	1/2	2
C4 Legal & Regulatory Uncertainty	1/3	1/4	1/2	1	1/3	2
C5 Economic & Strategic Risks	2	1/2	2	3	1	3
C6 Sustainability & Energy Consumption	1/3	1/4	1/2	1/2	1/3	1

For the first and second steps of the method, the criteria are determined and evaluated by the expert by comparing them with each other according to Saaty's comparison scale in Table 1, thus applying the first step of the method. The criteria evaluated according to the comparison scale are shown in Table 3. The column totals for the criteria are calculated in Table 4 by summing each column in the pairwise comparison matrix.

Table 4 Column sums for Criteria

C1	C2	C3	C4	C5	C6
5.166	2.833	9	13.5	3.666	15

Each column is normalized by dividing it by its own sum which is demonstrated in Table 5 according to Eq. 2.

Table 5 Normalized matrix

	C1	C2	C3	C4	C5	C6
C1	0.194	0.176	0.222	0.222	0.136	0.200
C2	0.387	0.353	0.333	0.296	0.545	0.267
C3	0.097	0.118	0.111	0.148	0.136	0.133
C4	0.065	0.088	0.056	0.074	0.091	0.133
C5	0.387	0.176	0.222	0.222	0.273	0.200
C6	0.065	0.088	0.056	0.037	0.091	0.067

The criterion weights are calculated by taking the average of each row using Eq. 3. These values provide the relative importance weights of the criteria.

Table 6 Criteria weights

C1	0.181
C2	0.335
C3	0.116
C4	0.078
C5	0.229
C6	0.062

The most important part of AHP is to check whether the decision maker is consistent. Consistency analysis checks consistency according to the E.4, Eq.5 and Eq.6.

$$\lambda_{max} = 6.15$$

$$CI = 0.03$$

$$RI(n = 6) = 1.24$$

$$CR \approx 0{,}024 \rightarrow \%2.42$$

Since the calculated value for CR is CR < 0.10, the matrix is considered consistent.

As a result of the recommended method, Cybersecurity & data management (A2) is the highest priority, Economic & strategic risks (A5) are second, Infrastructure & interoperability (A1) are third, Human factors (A3) and legal uncertainty (A4) are medium priority, and Sustainability & energy (A6) emerged as a lower priority.

Conclusion

In this study, the Analytic Hierarchy Process (AHP) was used to determine the importance levels of barriers related to Industry 4.0 applications in the Metaverse. The six fundamental barriers decided by the literature (i) infrastructure and interoperability, (ii) cybersecurity and data management, (iii) human factors and skills, (iv) legal and regulatory uncertainty, (v) economic and strategic risks, and (vi) sustainability and energy consumption—were evaluated using a pairwise comparison matrix. Comparisons were performed using Saaty's 1–9 scale, and normalized column averages, geometric mean, and, in particular, the principal eigenvector method were used to calculate priority vectors. When the obtained weights were ranked from highest to lowest, cybersecurity and data management (33.49%), economic and strategic risks (22.90%), and infrastructure and interoperability (18.09%) were identified as the most important barriers. For consistency assessment, the maximum eigenvalue ($\lambda\_max \approx 6.1500$), Consistency Index ($CI \approx 0.0300$), and Saaty's random index ($RI = 1.24$) were calculated, yielding a Consistency Ratio ($CR \approx 0.0242$). Since $CR < 0.10$, the decision-maker's comparisons were considered stable and consistent. As a result of the recommended method, Cybersecurity & data management (A2) is the highest priority. Data integrity, privacy, access controls, and security protocols appear to be the most critical obstacles in metaverse applications. Resource/strategy priority is recommended for this area. Economic & strategic risks (A5) are second: concerns about cost, investment risk, business model uncertainties, and strategic cost-benefit ratio are strong. Financial feasibility studies, pilot projects, and gradual scaling are recommended. Infrastructure & interoperability (A1) are third: network, low latency, edge/OT-IT integrations, and standards are important. Human factors (A3) and legal uncertainty (A4) are medium priority; training, competency development, and regulatory monitoring/compliance plans should be developed. Sustainability & energy (A6) emerged as a lower priority but should not be neglected in terms of long-term operational costs and public/customer perception; energy efficiency and green computing should be added to the roadmap.

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“Please review the following academic text from both a language and a technical aspect.

Language: Check grammar, punctuation, clarity, coherence, and formal academic tone.

Technical Accuracy: Evaluate whether the concepts, terminology, and methodology related to Multi-Criteria Decision Making (MCDM), Fuzzy Sets, and Fuzzy Logic are used correctly and appropriately. Assess the logical flow, problem framing, and suitability of the techniques within these subfields of industrial engineering.

If needed, suggest improvements in wording or technical precision without changing the intended meaning. If any parts are vague or methodologically weak, rewrite them.”

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CHAPTER 4

EU AND TÜRKİYE'S NATURAL GAS TARIFFS CONSIDERING UNDERGROUND GAS STORAGE SYSTEMS

1. Çetin Önder İNCEKARA[1]

Introduction

Gas storage plays a vital role in the global gas market, serving as a stabilizing buffer against imbalances caused by seasonal demand patterns and unexpected supply disruptions. Storage also helps mitigate market volatility during periods of price swings driven by external shocks, such as geopolitical events or natural disasters, by ensuring continuous and reliable gas supplies. Maintaining an adequate level of gas storage allows both consumers and suppliers to navigate periods of uncertainty, enhancing stability and resilience across the energy sector.

About one-quarter of all energy used in the EU comes from natural gas. Maintaining a secure supply is therefore essential to ensuring energy security for EU. Gas supply disruptions may result from technical or human failures, natural disasters, cyber-attacks and other emerging risks or geopolitical disputes. Many EU countries

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import nearly all their supplies and some are, or have been, also heavily reliant on a single source, meaning that disruptions along a single transport route can threaten the certainty of their gas supply. Since May 2022, the EU has taken a range of actions to eliminate its reliance on Russian fossil fuel imports by saving energy, diversifying supplies and accelerating the roll-out of renewable energy production in Europe.

Key progress on security of EU gas supply measures are taken in the first 3 years since the adoption of the REPowerEU Plan in May 2022 have reduced the volumes of imported Russian gas from 150 billion cubic meters (bcm) in 2021 to 52 bcm in 2024 which are:

-45% Share of EU gas imports from Russia in 2021

-19% Share of EU gas imports from Russia in 2024

-17% EU gas demand reduction August 2022 - January 2025

Although LNG imports from Russia increased by 2 bcm between 2023 and 2024, the end of the transit of Russian gas via Ukraine decreased the imports of pipeline gas from Russia by 15 bcm per year.

Reducing gas demand was a key part of the EU's successful response to the energy crisis and phase-out of its reliance on Russian fossil fuels under the REPowerEU plan of May 2022. EU emergency measures are:

-Emergency measures winter 2022/23

In response to EU unilateral supply cuts from Russia in the first half of 2022, in August 2022, the Council adopted an emergency Regulation on Coordinated Demand Reduction Measures for Gas (EU/2022/1369), introducing a voluntary reduction of natural gas demand for EU countries by 15% for winter 2022-2023. The regulation was proposed by EU Commission in July 2022 and also included the possibility for EU Council to trigger a ‘Union alert’ to trigger mandatory gas demand reductions in case voluntary measures were not enough to meet supply.

Along with its proposal of July 2022, EU Commission published EU Communication 'Save gas for a safe winter' (COM/2022/360), which included a European gas demand reduction plan to prepare the EU for supply cuts. EU Communication and its annex listed good practice measures to reduce demand and offered EU countries criteria to identify essential which were not already protected under EU Gas Security of Supply Regulation. In December 2022, EU Council also adopted a proposal from EU Commission on the temporary emergency Solidarity Regulation (EU/2022/2576), establishing among others default solidarity rules, extra safeguards for cross-border flows and critical gas volumes needed for gas-fired electricity generation.

-Emergency measures winter 2023/24

On 30 March 2023, amid persisting risks and challenges on the energy market, the Council adopted EU Commission’s proposal to prolong the coordinated gas demand reduction measures for a further 12 months to help avoid security of supply issues for winter 2023-2024 and fully compensate for the permanent decrease in Russian gas. The extension of the proposal also encouraged EU Commission and EU countries to monitor and report the data on savings per sector every month, rather than total gas demand every 2 months.

-Continued gas demand reductions

In February 2024, EU Commission published a report on the functioning of the Gas Demand Reduction Regulation. It showed that between August 2022 and December 2023, EU countries collectively reduced gas demand by over 100 billion cubic meters compared to the 5-year average, demonstrating the effectiveness of the voluntary measures. On this basis, EU Commission proposed a continuation of the voluntary gas demand reduction measures to help sustain and improve market stability and support the EU's decarbonisation efforts.

In March 2024, a Council Recommendation was adopted encouraging EU countries to continue taking voluntary measures until March 2025 to maintain a collective 15% gas demand reduction, compared to the average demand between April 2017 and March 2022.

Improved information exchange, regional cooperation and solidarity underpin the EU's framework for emergency preparedness and resilience to gas disruptions, as set out in the Regulation on measures to safeguard the security of gas supply (EU/2017/1938).

The framework legislates for

- cooperation between EU countries in regional groups to assess common supply risks (through common risk assessments) and to develop joint preventive and emergency measures

-the facilitation of permanent bi-directional capacity on all cross-border interconnections between EU countries by transmission service operators, unless an exemption is granted, the granting of exemptions are closely monitored by the Commission that can adopt decisions to request modifications to them

-the preparation of EU-wide simulations of gas supply and infrastructure disruptions, carried out by the European Network for Transmission System Operators for Gas (ENTSOG) to provide a high-level overview of the major supply risks for the EU

In line with the Regulation on Conditions for Access to the Natural Gas Transmission Networks (EC/715/2009), ENTSOG is also required to undertake seasonal supply outlooks investigating, at the pan-European level, the security of gas supply ahead of each winter and summer period. These seasonal supply outlooks help the Commission in its monitoring work.

On 5 September 2012, the EU Agency for Cooperation of Energy Regulators (the ‘Agency’) launched a public consultation on the draft Framework Guidelines rules regarding harmonised transmission tariff structures for gas. The purpose of this consultation was to collect the views of the stakeholders in order to develop the Framework Guidelines (the “FG”) pursuant to Articles 6(2) and 8(6)(k) of Regulation (EC) No 715/2009 (the “Gas Regulation”).

The public consultation launched by the Agency solicited feedback from various stakeholders on the draft Framework Guidelines as published on 5 September 2012 on the Agency’s website. The public consultation closed on 5 November 2012. In addition to the consultation, an Open House was conducted on 4 February 2013. Annex 2 contains stakeholders’ views from the Open House submissions and the Agency’s summary of the additional comments received in writing. Annex 3 provides the list of respondents to the Open House.

The Energy Code empowers the Energy Regulation Commission (CRE) to define the methodology for establishing tariffs for the use of natural gas transmission networks, gas storage facilities and LNG terminals. CRE can make changes to the tariff levels and structure deemed justified in light of operators’ accounts and any expected changes in operating or investment expenses.

Natural gas network tariffs are calculated using income and expense assumptions for the different elements covered by tariffs. An ex-post adjustment mechanism, the expenses and revenue claw-back account, helps to resolve differences between actual expenses and income and projected expenses and income for elements which are difficult for gas system operators to predict and control. To encourage operators to control energy expenses (gas and electricity) and CO_2 allowances, only 80% of the differences of those costs compared to the previous year's updated energy expenses trajectory are covered by this mechanism. The remaining 20% of this difference is for the benefit or at the expense of the operator to encourage them to stay below the defined trajectory.

Considering EU Regulation numbered 2017/460, which establishes a network code setting out the rules on harmonised transmission tariff structures for gas, CRE deliberated on tariffs for natural gas transmission systems, storage facilities and LNG terminals. These tariffs address a number of objectives, including proper functioning of the wholesale gas market, supporting the energy transition by enabling biomethane injection, and ensuring proper safety and environmental standards.

In October 2024, the Commission publicly launched the interactive security of gas supply dashboard. It provides comprehensive weekly data on imports, storage levels, transport and consumption of gas in the EU, allowing national and EU decision-makers take swift and informed actions to ensure energy security across the EU.

On 23 March 2022, the Commission published a Communication on security of supply and affordable energy prices (COM/2022/138), together with a proposal for a new regulation on gas storage. The Gas Storage Regulation (EU/2022/1032) was adopted in June 2022 and applies until the end of 2025.

On 5 March 2025, in the context of continued volatility and uncertainty in the global energy landscape, the Commission proposed to prolong the regulation for 2 years (COM/2025/99), until the end of 2027, following its report on the regulation (COM/2025/98).

On 5 March 2025, the Commission published a recommendation (C/2025/1481) to EU countries to consider the current market conditions and introduce flexibility when deciding on measures to refill their storages next summer.

On 17 July 2025, the Commission published a 4 week call for evidence on a draft delegated regulation updating the composition of risk groups as foreseen in Regulation (EU) 2017/1938. It reflects the significant changes to EU gas supply since 2021 and the evolution of the major transnational risks to security of gas supply. The draft delegated regulation maintains 4 risk groups but introduces significant simplification. EU countries were consulted through the Gas Coordination Group (GCG), and there will be a further consultation of the GCG following the public call for evidence.

EU Parliament and the Council reached a provisional agreement on the Commission’s proposal in June and the adopted Regulation EU/2025/1733 was published on 10 September 2025.

Gas storage, in particular Underground Gas Storage (UGS), is instrumental to the security of supply as it provides an additional reserve in case of strong demand or supply disruptions. Typically, storage provides 25-30% of gas consumed in the EU during winter. It reduces the need to import additional gas and contributes to absorbing supply shocks.

What is UGS Tariff?

Underground Gas Storage (UGS) tariff is based on the specific requirements of customers and within the bandwidth of the technical specifications of its facility. Therefore, a standard ratio between Send In capacity, Send Out capacity and Working Gas Volume is not applicable in the market. All services are customized and tariffs are established through negotiations. And it affects the natural gas tariff directly.

EU's gas companies publish the weighted average tariff for a service on TTF with an average bundle ratio for relevant storage year. The below tariff excludes energy charges and includes transportation charges.

-The average tariff for storage year 2023 is € 14.84 Euro/MWh for the average bundle of 0.66/1/259.

-The average tariff for storage year 2024 is € 16.13 Euro/MWh for the average bundle of 0.75/1/341.

Around 2006 most of EU countries' Authorities for natural gas approved the Storage Code Resolutions. EU tariff for injection, storage and withdrawal of gas are stated by countries' natural gas distribution companies.

In Turkey, Energy Market Regulatory Authority (EMRA) has announced the storage and transmission tariffs for storage facilities, i.e. BOTAS's Tuz Golu Underground Natural Gas Storage Facility and Silivri Underground Natural Gas Storage Facility.

For the year 2025, storage year, the upper limit storage fees were set by EMRA:

- 3.080123 TL per cubic meter for capacity fees,

- 0.105722 TL per cubic meter for injection fees,

- 0.010516 TL per cubic meter for withdrawal fees.

Best Practice Guidelines for the Implementation of the Pass-Through Mechanism for gas costs, Trading Hub Europe publishes the specific gas pass-through amount that is applicable across EU's countries. The gas pass-through amount is charged in addition to the transportation tariffs at exit points to the Transmission System Operator-TSOs' directly connected final consumers and downstream network operators. Exit points to storage facilities as well as cross-border and market area interconnection points are taken into account.

UGS plays an important role to balance the EU and Türkiye's natural gas system and to cover peak demand during winter. Gas storages play an important role for ensuring continuity of gas supply; it is an important source of gas flexibility during the winter and are refilled during the summer period. The role of storages becomes more relevant in a context where the EU indigenous gas production consistently declines year on year, increasing the gas import dependency from external gas producers to the EU. The UGS inventory level on 1 October 2021 is the lowest of the past 5 years, and it has continued below the average during the winter of 2021-2022. This is primarily due to a low storage level at the end of winter 2020-2021, combined with a storage injection season characterised by extremely high gas wholesale prices which did not incentivize market participants to store gas in comparison to previous years.

EU Gas Storage Regulation

Under EU Gas Security of Supply Regulation (EU/2017/1938), amended by the Gas Storage Regulation (EU/2025/1733), gas storage facilities are considered critical infrastructure and an updated certification process was introduced for all storage operators in the EU to reduce the risks of outside interference. This contributes to reducing the security of supply risks and supports the EU's competitiveness by ensuring that storage facilities are properly filled.

Operators of storage sites should report the filling levels to national authorities and EU countries should monitor the filling levels on a monthly basis and report to the EU Commission.

Another important element is the burden-sharing mechanism. Some EU countries have storage larger than their own national consumption, while others do not have any storage facilities. However, all EU countries benefit from the guaranteed filling levels, so the burden-sharing mechanism makes sure that not only EU countries with storage facilities pay for the security of supply costs of the minimum filling target.

To ensure security of gas supply and to comply with the gas storage target of 90% each year, EU countries with underground gas storage facilities define the intermediate targets for the 1st of February, May, July and September. The trajectories are based on the filling rates of the previous 5 years, and the Commission and EU countries regularly monitor the storage filling trajectories within the Gas Coordination Group.

EU Gas Storage Levels

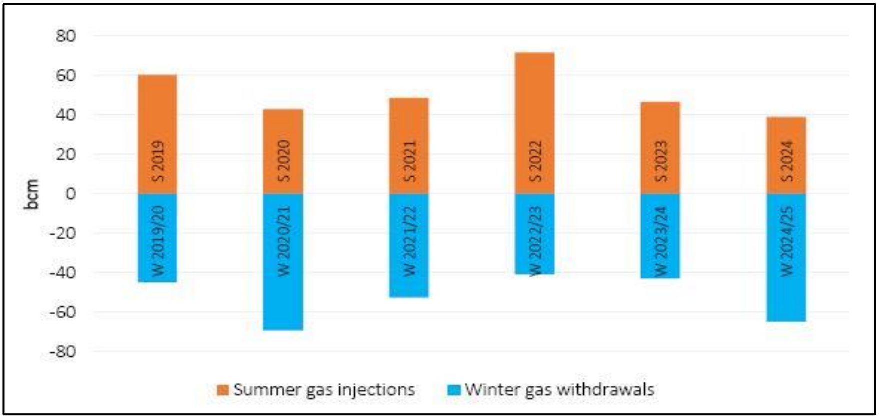
EU is the world's second largest region in terms of underground gas storage (UGS) capacity, behind US. EU member states collectively operate UGS sites with a working gas capacity of 104 bcm, accounting for one quarter of the global capacity. The importance of gas storage in the EU has grown significantly since the 2022 energy crisis, underscoring the need for supply security and system flexibility. Storage is especially critical given the region's sharp seasonal demand swing, with winter gas consumption rising by approx. 135% compared to the summer. This contrasts with a 50% seasonal increase in US and just 11% in China, highlighting the EU's heightened dependence on storage for winter supply reliability.

EU gas system reached a storage level of 83% on 1 October 2025, recording approximately 85 bcm of gas in stock at the start of the winter. This level is in the range observed in the years prior the energy crisis and represents around 25% of the EU's annual gas consumption. Starting from a 34% filling level on 1 April 2025, 50 bcm of gas was injected into EU gas storages during the summer to reach current levels. This is substantially more than in the previous 2 years.

In June 2022, the EU underwent a structural shift in its gas market framework with the adoption of Regulation (EU) 2022/1032, aimed at ensuring stable gas supply in winter seasons. This regulation introduced three key measures for EU member states to enhance gas storage security. First, it set binding capacity targets for UGS sites: storage facilities were to be filled to at least 80% by 1 November 2022, increasing to 90% by 1 November in subsequent years. Intermediate targets were also established throughout the year, specifically at the start of February, May, July and September. Second, the regulation limited the required filling volume to 35% of the member state's average annual gas consumption over the previous five years.

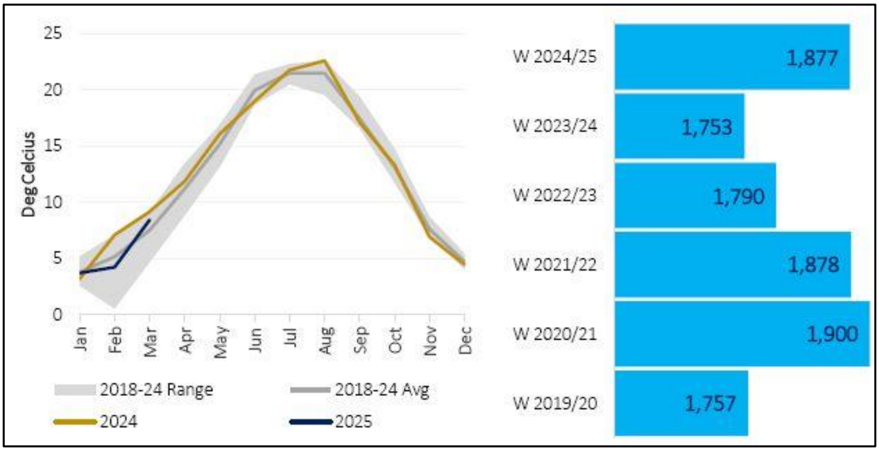
The new EU regulation prompted EU member states to inject a record 72 bcm into UGS facilities during the 2022 summer season, following a historically low end-of-winter level of just 26 bcm. That enabled the region to maintain a reliable gas supply throughout the 2022/2023 winter. In both 2023 and 2024, the EU encountered fewer challenges in meeting its intra-year storage targets, owing to a combination of factors: milder-than-expected winter weather, declining gas demand, robust LNG imports, and stabilised pipeline gas imports. These conditions contributed to net gas withdrawals of just 41 and 43 bcm over the two winter seasons, the lowest levels in over a decade. By the end of the 2023/2024 winter, gas storage remained at an all-time high of 61 bcm. As a result, gas injection needs during the 2024 summer season were significantly reduced, with only 39 bcm injected, marking a record low since 2012 which is presented in Figure 1.

Figure 1. UGS injections and withdrawals in EU



After two consecutive winters of milder-than-average temperatures, the 2024/2025 winter marked a return to colder weather conditions, last seen three years ago. Net gas withdrawals began as early as 22 October 2024, more than two weeks earlier than in 2023, and average EU temperatures remained below historical norms throughout the winter. During the core winter months (November 2024 to March 2025), the average temperature in the EU dropped to 5.6°C, significantly lower than 6.5°C in 2023/2024 and the average of the previous six winters of 6.0°C. This is supported by heating degree days (HDDs) data, which measure heating demand by calculating the difference between the mean daily temperature and a reference temperature. Over the 2024/2025 winter season, the EU recorded a total of 1,877 HDDs, representing a 7% increase compared to the previous winter and a 3% increase over the average of the prior six winter seasons which is presented in Figure 2.

Figure 2. Average EU temperatures (L) & heating degree days (R)



Below-average temperatures during the 2024/2025 winter posed challenges to the supply-demand balance in the regional gas market. On the demand side, colder weather led to a significant increase in gas consumption for heating, with the region estimated to have consumed 16 bcm more than during the previous winter.

On the supply side, the EU experienced reduced gas availability, driven by declines in both domestic production and gas imports. Domestic output continued its structural downward trend due to depleting reserves, with the total domestic EU output declining from 17 bcm in the 2021/2022 winter to 12 bcm in the 2024/2025 winter, hence, further intensifying the region's dependence on external supply. However, pipeline gas imports during the winter season fell sharply by 42 bcm over the past three years, from 104 bcm in 2021/2022 to 62 bcm in 2024/2025, largely as a result of geopolitical developments. This decline was only partially offset by a 12 bcm increase in LNG imports during the winter season, rising from 43 bcm in 2021/2022 to 55 bcm in 2024/2025. Consequently, total EU gas imports dropped to 117 bcm during the 2024/2025 winter, down from 121 bcm in 2023/2024, 123 bcm in 2022/2023 and 147 bcm in 2021/2022, further aggravating the region's supply situation amid heightened seasonal demand.

With the supply-demand balance tightening, EU was forced to rely on UGS withdrawals during the 2024/2025 winter as a critical component of gas supply, with withdrawals reaching 65 bcm, a level not seen since 2020/2021. As a result, storage levels fell to just 35 bcm by the end of the winter season. While this is only slightly below the 10-year average of 38 bcm, it is significantly lower than the levels recorded in 2024 (61 bcm) and 2023 (57 bcm), making the current gas storage situation markedly different and considerably more complex.

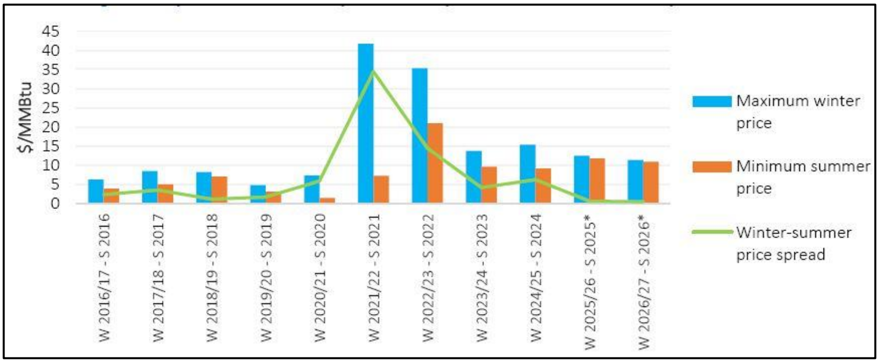
By 1 November 2025, under the current gas storage regulations, EU member states must restock approximately 60 bcm to meet the 90% capacity target. This figure is significantly higher than the volumes injected during the 2023 and 2024 summer seasons, which amounted to 47 bcm and 39 bcm, respectively.

The common expectation is that EU will succeed in injecting the required storage volumes, however, compliance with mandatory storage targets is likely to lead to elevated prices, as was the case during the 2022 energy crisis. At that time, Europe, urgently seeking LNG to offset declining pipeline gas imports, emerged as a premium destination for global LNG, overtaking Asia. This was reflected in European hub prices surpassing Asian spot LNG prices, marking an unprecedented reversal of the traditional inter-regional price relationship. As market conditions stabilized, the NEA-TTF price spread gradually returned to historical norms, with Asia regaining its premium over Europe in 2023 and 2024. In 2025, as Europe once again demands higher LNG volumes to refill UGS sites, and therefore competes with Asia for spot LNG cargoes, TTF spot prices are expected to remain elevated throughout the summer. Additionally, lower-than-expected LNG demand in China and US-initiated tariff war may exert downward pressure on spot LNG prices in both regions.

There is a strong correlation between gas prices and storage dynamics in EU market. During the winter months, colder temperatures drive up heating demand, leading to higher gas consumption and a corresponding increase in prices. Conversely, in the summer, heating demand declines sharply, resulting in lower consumption and typically lower prices. This seasonal pattern generates a winter-summer price spread, incentivizing market operators to buy gas at lower summer prices, inject it into UGS sites, and resell it in winter at higher prices.

Considering the maximum average monthly TTF price during the winter months versus the minimum average monthly TTF price during the summer months, the seasonal price spread averaged \$2.9/MMBtu between 2016 and 2020 (Figure 3). Amidst the post-pandemic recovery and the 2022 energy crisis, the spread widened to an unprecedented \$35/MMBtu in 2021 and \$14/MMBtu in 2022, and remained at an economically effective level of \$4–6/MMBtu in 2023 and 2024. However, in 2025, futures price dynamics indicate a slightly positive winter-summer price spread of just \$0.7/MMBtu, as the EU's gas storage regulations are expected to support high injection demand, exerting upward pressure on prices. At the same time, the global gas market is expected to see increased supply by year-end, with 54 Mtpa of new liquefaction capacity coming online throughout 2025 and production ramping up by year-end, which is likely to suppress any significant rise in winter prices. As a result, the narrow seasonal price spread is expected to lead to commercial losses for gas storage operations.

Figure 3. Spread between the peak winter prices and lowest summer prices in the EU



Regulation (EU) 2022/1032 was initially set to expire at the end of 2025, but in March 2025, the European Commission proposed a two-year extension, through the end of 2027, emphasizing its continued importance for ensuring both gas supply security and market stability. At the same time, the Commission is reviewing proposals from several member states seeking greater flexibility within the regulatory framework, particularly by allowing 10% deviations from storage targets and compliance deadlines under exceptional national circumstances. Looking beyond 2027, EU gas market is expected to evolve toward a more balanced and resilient structure, potentially reducing the need for such administrative.

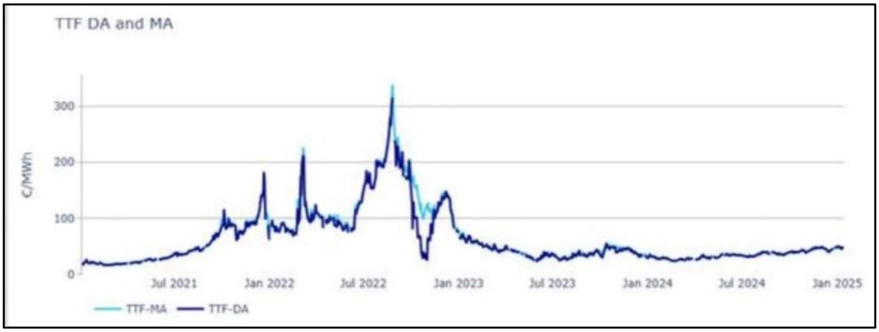
The original Gas Storage Regulation, 16 in force since 1 July 2022, included the following key requirements:

• A mandatory storage filling obligation, stipulating a binding final filling target and filling trajectories with intermediate targets as well as storage burden-sharing mechanisms (initially codified by amending the Security of Supply Regulation);

• mandatory certification of storage operators (codified by amending the Gas Regulation 715 and subsequently incorporated into the Renewable and Natural Gas and Hydrogen Regulation).

The Regulation's requirement for EU Member States to meet the final filling target and to adhere to filling trajectories with intermediary targets was a highly interventionist measure, adopted amidst the energy crisis of 2022 when fears ran high that EU gas storage would not be filled ahead of the winter of 2022- 23. While it ensured storage was refilled, it also contributed to a sharp increase in gas prices in the 3Q2022, as all Member States simultaneously scrambled for supplies to meet their targets (Figure 4).

Figure 4. TTF day-ahead and month-ahead prices, euros/MWh



While the Regulation was set to expire at the end of 2025, it contained a provision which envisaged the possibility of mandatory filling targets and trajectories becoming permanent as part of the Gas Security of Supply Regulation review, based on the EC report.

Türkiye's UGS Facilities

Türkiye's UGS Facilities and their capacities are listed below:

-Tuz Golu Underground Natural Gas Storage Facility: It is located in the Aksaray province, 40 km South of Tuz Gölü in the Sultanhani district of Türkiye. In 2011 construction work was started and it is aimed to reach 5.4 bcm total storage and 80 million Sm^3 daily withdrawal capacity together with Gas Storage Expansion Project. Today 1,2 billion Sm^3 working gas capacity and 40 million Sm^3 daily withdrawal capacity have been reached. (www.botas.gov.tr)

-Değirmenköy Onshore Natural Gas Storage Facility: One of the depleted underground gas storage of Türkiye is Degirmenkoy field. The Degirmenkoy is one of the two reservoirs of Silivri underground natural gas storage facility. The field is located in the Thrace region of Turkey. It is an onshore gas field located 16 km northern-west of the Northern Marmara field. The storage capacity of the Değirmenköy Reservoir is 300.000.000 m3 (www.botas.gov.tr).

-Northern Marmara Offshore Natural Gas Storage Facility: The Northern Marmara Gas Field was discovered in 1988 in an area 5 km west of Silivri and 2.5 km far off the coast at a depth of 1,200 m. To determine the size of the natural gas reserve, which is the first undersea natural gas reserve in Turkey, three offshore boreholes in 1995 and two more were drilled in 1996. Natural gas production started in September 1997 at the five gas wells. Gas was pumped from an offshore platform by a 3 km-long undersea pipeline to the plant at the coast for processing. The storage capacity of the Northern Marmara Reservoir is 1.600.000.000 m3 (www.botas.gov.tr).

Currently, the Northern Marmara and Değirmenköy (Silivri) Depleted Gas Reservoir is the only underground natural gas storage facility in Turkey. Northern Marmara-Değirmenköy Storage Facilities in the Silivri district of Istanbul has 3,19 billion Sm^3 storage and 28 million Sm^3 daily withdrawal capacity, and with the project initiated in 2017, it aims to reach 4.6 billion Sm^3 storage and 75 million Sm^3 daily withdrawal capacity via Phase-I and Phase-II Projects. It is planned that the total storage capacity will be 4,29 billion Sm^3 working gas capacity (www.botas.gov.tr).

EU's UGS Facilities

Eighteen EU Member States – Austria, Belgium, Bulgaria, Czechia, Germany, Denmark, Spain, France, Croatia, Hungary, Italy, Latvia, the Netherlands, Poland, Portugal, Romania, Sweden, Slovakia – have underground storage capacity. Total EU storage capacity stands at ~105 bcm in 2025 (equating to slightly less than one third of annual EU consumption during 2020-24) but is distributed unevenly across different Member States. Final filling targets for 2022, 2023, and 2024 have been met by all EU Member States, with many of them exceeding this target.

The original EU Regulation obliged EU Member States to fill their gas storage to at least 80 per cent of capacity by 1 November 2022 and to at least 90 per cent of capacity by 1 November of 2023, 2024, and 2025, known as the 'final filling target'. This requirement applied to all underground storage facilities located on their national territory and directly interconnected to a market area in their national territory.

EU Regulation also stipulated that by 15 November of each year while it was in force, EC had to set a filling trajectory for each Member State for 2023, 2024, and 2025 (with intermediary targets for 1 February, 1 May, 1 July, and 1 September) based on draft filling trajectories, which had to be submitted by Member States to the EC by 15 September each year. The Regulation specified that Member States' draft filling trajectories had to be based on the average filling rate during the preceding five years. Given that EU filling level was significantly elevated during the 2022-23 and the 2023-24 filling seasons compared to pre-crisis levels, the average filling rate used for developing the draft filling trajectory for each subsequent season was skewed upwards.

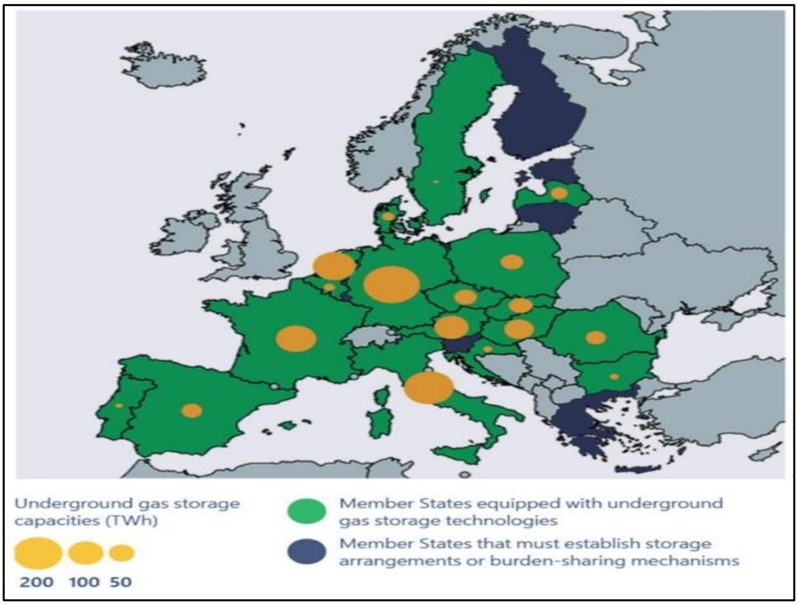
EU Regulation allowed Member States to meet the final target partially by counting LNG stored and available in their LNG terminals (Art. 6a.5), if

a. such LNG storage capacity accounted for more than 4 per cent of their average consumption over the preceding five years on an annual basis, and

b. an obligation on gas suppliers to store minimum volumes of gas in underground storage facilities and/or LNG terminals was in place with Spain and Portugal qualifying for this derogation. Application of these derogations meant that for exempted Member States the final filling targets for 1 November 2025 were significantly lower than the default filling target of 90 per cent of capacity.

Several EU Member States – Estonia, Ireland, Lithuania, Greece, Cyprus, Slovenia, Finland, Luxembourg, and Malta – do not have any underground storage facilities. Member States without such facilities are obliged to establish storage arrangements to store gas in, or conclude burden-sharing agreements with, Member States which have underground storage facilities. (Figure 5)

Figure 5. Member States: storage filling requirements, storage arrangements, and burden sharing



The EU faces a triple challenge, to ensure the security of gas supply and, at the same time, to secure affordability and accelerate the decarbonisation of the gas sector.

The green transition of the European gas market and the move towards new and renewable gases is not only a challenging undertaking but also an opportunity to:

• Ensure environmental sustainability of the European gas sector;

• Enable competitiveness and affordability by creating a more stable supply of gas;

• Secure the autonomy of the EU from gas imports and reduce dependencies on individual third countries.

EU's gas storage rules 2025-2027; the main changes to the extended regulation are:

-A 2-month period to meet the 90% filling target every year (1 October – 1 December), replacing the 1 November deadline

-the nature of gas filling trajectories is indicative, unless decided otherwise by EU countries

-EU countries have the flexibility to deviate from the gas filling target in case of difficult market conditions or technical constraints

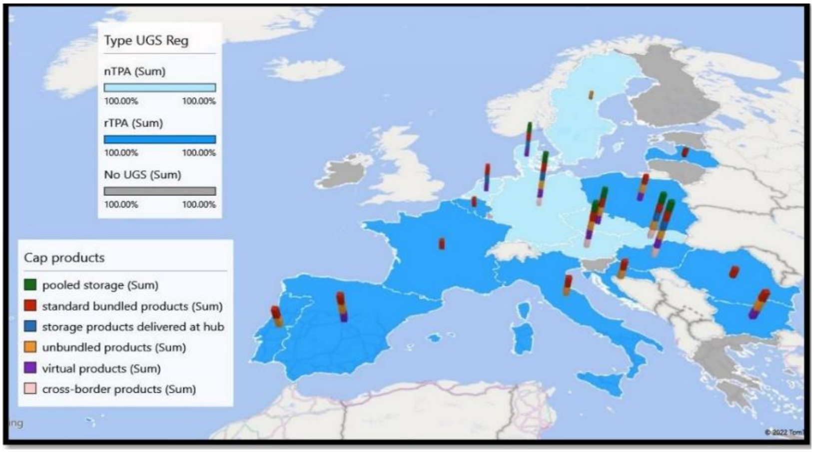
-EU Commission has the possibility to further reduce the target, if unfavourable market conditions persist

Most gas storage capacity in EU corresponds to depleted and aquifers fields, which are mainly used to store large volumes of gas to balance seasonal swings of gas demand and to the extent possible also for short-term trading and balancing. All EU but Portugal and Sweden report having depleted and/or aquifers storage sites. In addition, 8 EU member count with salt and hard rock caverns storages, representing a low but varying percentage of the total storage capacity. Caverns are primarily used to optimise gas portfolios in the short term as they typically allow for several gas injection and withdrawal cycles per year. In Portugal, salt caverns allow for multiple uses, including seasonal storage. Salt and hard rock caverns are available in Czechia (2% of total storage capacity), Denmark (45%), France (10%), Germany (50%), Netherlands (3%), Poland (26%) and Portugal (100%). This information is generally consistent with GIE data (see Table 3) which contains details on the WGV capacity per type of storage.

As regards the responsibility for monitoring the compliance with Gas In Storage (GIS) obligations, where applicable, there are different models. In all cases there is regular monitoring from the SSOs. In the case of all regulated storages and for most negotiated storages, SSO report to public authorities (Ministries, NRAs) and in some instances also to oil and gas national stockpiling associations (Hungary and Spain). Most NRAs from EU countries with negotiated storages (Austria, Denmark, Germany, Latvia, Netherlands and Sweden) have not identified actors responsible for compliance, as GIS obligations are not applicable. However, NRAs with negotiated storages may also receive regular information on storage filling levels and contracts (e.g. Austria, Germany confirmed, and possibly others).

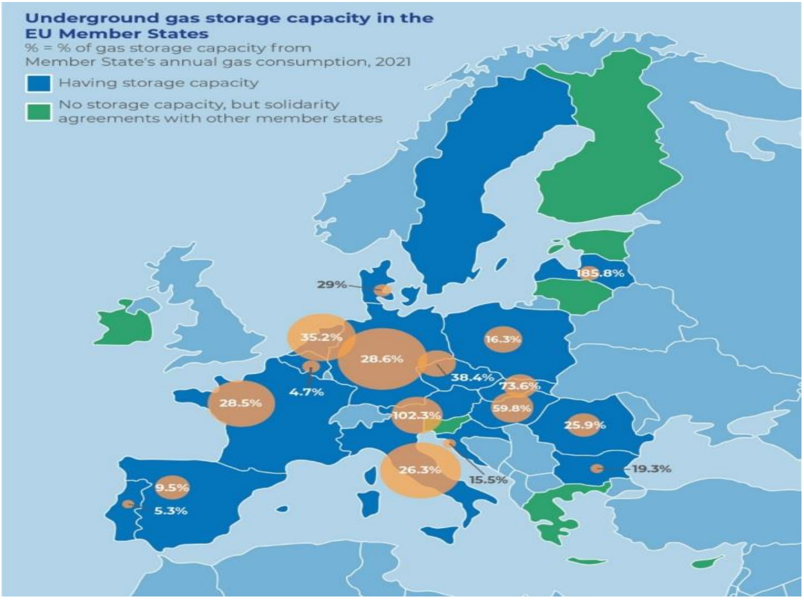
The availability of storage capacity products ranges from a single standard bundled product to up to six different products. All but one NRA reported that the storage system operators (SSO) offer standard bundled products, while 12 NRAs responded that SSOs were offering unbundled products. 9 NRAs selected virtual products, 5 inform of the existence of storage products delivered at the hub (Denmark, Germany, Hungary, Netherlands, Slovakia). Pooled storages are used also in 6 EU Countries (Austria, Czechia, Denmark, Germany, Hungary, Slovakia) and cross-border products are apparently only available in Austria, Germany, Hungary and Slovakia. NRAs report that 10 EU Countries offer three or more types of capacity products, and all 6 type of capacity products are available in Germany and Hungary.

Figure 6. Availability of capacity products and type of storage regulation



Total EU gas storage capacity, or working gas volume ('WGV'), is 1141 TWh (approx. 100bcm), or about 27% of the EU-27 annual gas consumption. Gas storage supplies about 25-30% of the gas consumed in the EU during winter 207, Figure 7 shows the allocation and size of Member States' storage capacity and the share of their annual gas consumption it can cover.

Figure 7. Gas storage capacity in the EU Member States



NRAs from Member States which opted for a regulated regime for storage (e.g. Belgium, France, Italy, Poland and Spain) have a positive assessment of their national systems and note an adequate storage filling level at the start of current winter season. In Portugal, the filling levels were low in October (50%) but they recovered by December 2021 (80%). In Portugal, it is not a typical that storage levels are lower in October as gas demand for power generation is higher during the summer. NRAs from EU Countries with negotiated storage do not deem that regulatory intervention would be necessary and, in some cases (Austria, Slovakia) note that the available storage capacity is used also by gas traders and gas suppliers of adjacent Member States, not necessarily correlating low storage levels in their territory with a serious concern for national gas consumers.

Gas in storage levels are subject to regular monitoring by the SSOs, network operations and most NRAs. The majority of NRAs, despite noting that the vigilance over gas storage levels has increased, and do not report that current Gas In Storage (GIS) levels are a concern. In fact, there are limited ongoing discussions at national level to propose to maximise the GIS levels. Only ACM (for the Netherlands) reports current concerns focused on GIS for high calorific value gas (H-gas) storages and ongoing political discussions around plans for setting minimum storage obligations, and Ei (for Sweden) makes reference to an ongoing discussion with gas suppliers to commercially fill the storage in Sweden and the GIS levels in neighbouring Denmark. NRAs from Member States which opted for a regulated regime for storage (e.g. Belgium, France, Italy,Poland and Spain) have a positive assessment of their national systems and note an adequate storage filling level at the start of current winter season. NRAs from MS with liberalised storage do not deem that regulatory intervention would be necessary and, in some cases (Austria, Slovakia) note that part of the available storage capacity is used by gas traders and suppliers of adjacent Member States, not necessarily correlating low storage levels in their territory with a serious concern for national gas consumers.

Natural Gas Tariffs Elements considering UGS systems

The main elements of natural gas tariffs considering UGS are;

1) Allowed revenue (AR);

2) Operating and maintenance expenditures (OPEX);

3) Gas losses;

4) Regulated asset base (RAB) and return on the RAB;

5) Depreciation;

6) Administrative provisions (amendment of tariffs, tariff methodology...)

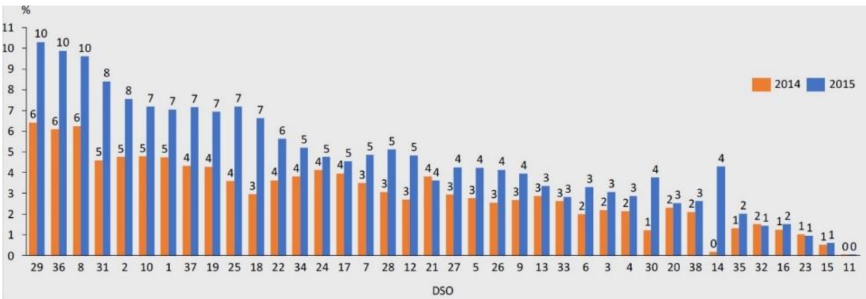
7) Storage fees (capacity fees, injection fees, withdrawal fees)

Allowed revenue (AR): AR cover prudently incurred operating costs (incl. costs of gas losses), depreciation and amortization of the regulatory asset base (assets used to provide the gas distribution service) and the return on the regulatory asset base less other revenue.

Operating and maintenance expenditures (OPEX): OPEX consists of labor costs, material costs, gas losses, service costs.

Gas losses: In EU NRA prescribe the maximum allowed amount of gas losses and unit price based on a benchmark comparing all DSOs.

Figure 8. The maximum allowed amount of gas losses and unit price based on a benchmark comparing all DSOs



Regulated asset base (RAB) and return on the RAB: Asset financed by the DSO used in the distribution activity (land, equipment, buildings, non tangible assets) It increases with investments and decreases due to depreciation/amortization. Investments include those investments included in the investment plan.

Depreciation: Depreciation and amortization calculated for assets is used for the gas distribution activity, and it does not include assets received free of charge financed by third parties. Depreciation and amortization of assets is calculated using straight line depreciation method. Depreciation and amortization rates are calculated assuming useful life of assets.

Administrative provisions (amendment of tariffs, tariff methodology...): EU's tariff methodologies are mainly diverse methodological approaches that are listed below:

- Cost-plus: the NRA sets a tariff based on the reported operating costs and the return on capital. No "extra profit" foreseen.

- Incentive regulation: tariff are set on a decreasing trajectory. DSOs are incentivized to reduce their costs by being allowed by the NRA to keep part of the savings.

Tariffs are set for regulatory periods, which last for 4-5 years (no prescribed length) Common distribution tariff elements are; Annual consumption, Pressure level, Used capacity, Geographic zones.

Possible natural gas tariff items are: A fixed charge expressed as EUR / month / consumer that is constant for all the consumer or for a class of consumers → It reflects the cost of metering, meter maintenance and meter replacement; Variable charge expressed as EUR/kWh that depends upon the amount of gas distributed to each consumer; A capacity charge expressed as EUR / kWh/h commensurate to the amount of capacity for each consumer. It is usual to have a combination of fixed and variable charge. The drawback of a capacity charge as that it is not metered and it depends on the capacity of the connection.

Storage fees (capacity fee, injection fee, withdrawal fee): The upper limit storage fees are set by national energy regulatory authority (NRA) via DSOs. Distribution System Operators (DSOs) are responsible for:

-Operating, maintaining and developing (if necessary) the distribution system and providing secure, reliable and efficient services to the customers;

-Liaising and working with other participants on the natural gas market such as transmission system operators and operators of underground gas storage facilities or LNG terminals;

-Providing open and transparent transport services to system users i.e. to end-suppliers and to customers;

Related to distribution, the national energy regulatory authority (NRA) is responsible for:

-Fixing or approving the methodologies for calculating and/or the tariffs for distribution services incentivizing DSOs to increase efficiencies, foster market integration and security of supply;

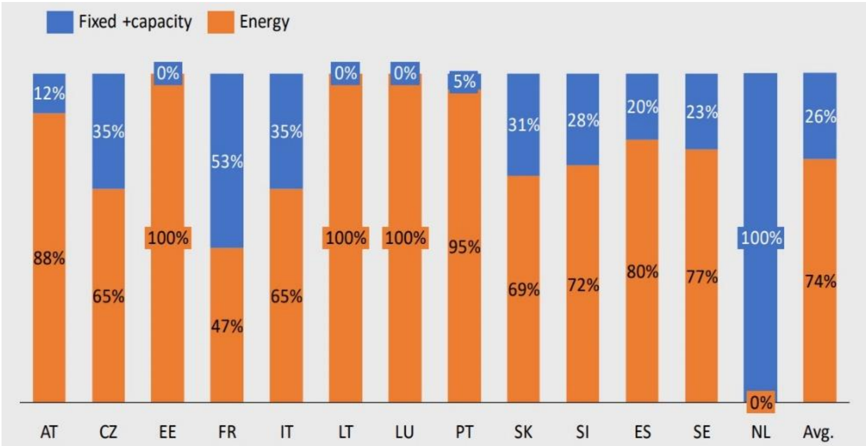
-Ensuring that DSOs operate in compliance with national and Energy Community rules;

-Ensuring that there are no cross-subsidies between distribution and other activities;

-Setting or approving standards related to the quality of distribution services and monitoring time taken by DSOs for adding new connections or carrying out repair works;

-Helping to ensure that consumer protection measures are put in place and process customer complaints vis-àvis the DSO.

Figure 9. Distribution of gas tariff fee in EU.



Material and Method

In the study; an integrated Fuzzy AHP-Fuzzy TOPSIS- Fuzzy VIKOR approaches are used to assess/evaluate natural gas tariffs elements considering UGS systems. In literature Fuzzy Multi Criteria Decision Making Methods (FMCDM) are used in different fields by many researchers [1-42] by using MATLAB program.

Fuzzy Multi Criteria Decision Making Methods (FMCDM)

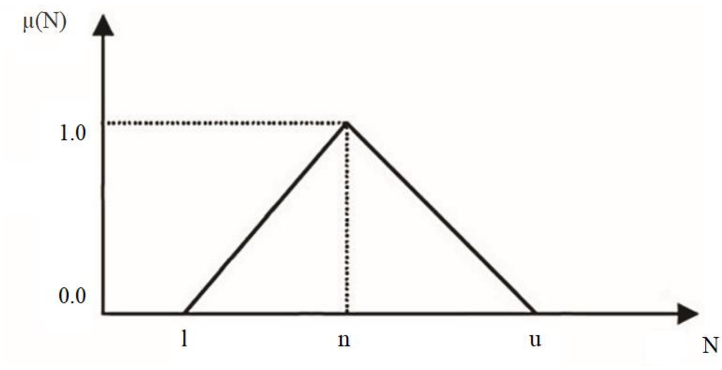
In literature Fuzzy Multi Criteria Decision Making Methods (FMCDM) are used in different fields by many researchers and fuzzy methods are also used in many sectors, i.e. to evaluate design parameters, to evaluate models, to evaluate the criteria for human resource for science and technology, for analyzing customer preferences, to evaluate risk analysis in green supply chain, and to select machine tools. In the study; an integrated Fuzzy AHP-Fuzzy TOPSIS- Fuzzy VIKOR approaches are used to assess/evaluate natural gas tariffs considering underground gas storage systems.

Fuzzy AHP Method

Since the standard AHP method does not include the possibility of situations with ambiguity in the estimation, it is possible to upgrade this method with fuzzy approach. This approach is called the Fuzzy AHP method. Instead of one defined value, in the Fuzzy AHP method full range of values that include unsafe attitudes of decision maker should be generated. For that process it is possible to use triangular fuzzy numbers, trapezoidal or Gaussian fuzzy numbers. The Fuzzy AHP method suggests their application directly in criteria pairs comparison matrix. Triangular fuzzy numbers are used in most cases/problems by many researchers in literature because of this reason in the study triangular fuzzy numbers method is used in Fuzzy AHP method. A triangular fuzzy number that is defined in R set can be described as Ñ= (l, n, u) where l is the minimum, n is the most possible and u is the maximum value of a fuzzy case. Its triangular membership function is characterized below which is presented in Figure 10 and in equation (1).

$$\mu\tilde{N}(x) = \begin{cases} (x-l)/(n-l), & l \le x \le n \\ (x-u)/(n-u), & n \le x \le u \\ 0, & x < l \text{ or } x > u \end{cases} \quad (1)$$

Figure 10. Triangular fuzzy number



Triangular fuzzy number Ñ (shown in Figure 10) can be described as an interval of real numbers where each of them has a degree of belonging to the interval between 0 and 1. Triangular fuzzy number is defined with three real numbers, expressed as l, n and u. In the study the performance of each scenario to each criterion is introduced as a fuzzy number. And in the study the ratings of qualitative criteria are considered as linguistic variables. These linguistic variables can be expressed in positive triangular fuzzy numbers as described in Table 1.

Table 1. Linguistic Variables for the Alternatives

Linguistic Terms-Abbreviation	**Linguistic Variables**	**Triangular Fuzzy Numbers**
SDA	Strongly Disagree	(0, 0, 0.15)
DA	Disagree	(0.15, 0.15, 0.15)
LDA	Little Disagree	(0.30, 0.15, 0.20)
NC	No Comment	(0.50, 0.20, 0.15)
LA	Little Agree	(0.65, 0.15, 0.15)
A	Agree	(0.80, 0.15, 0.20)
SA	Strongly Agree	(1, 0.20, 0)

After forming a matrix of fuzzy criteria comparison it should be defined vector of criteria weights W. For that purpose, the following equations/steps were used in the study.

Let X ={x1, x2,..., xm } be an object set, and G={g1, g2,...,gn} be a goal set. N extent analysis values for each object can be obtained as $N_{gi}^{1}, N_{gi}^{2}, \ldots, N_{gi}^{n}$ i= 1,2,…n

Step 1: The values of fuzzy extensions for the i-th object are given in Expression (2);

$$Si = \sum_{j=1}^{n} N_{gi}^{j} \otimes \left[\sum_{i=1}^{m} \sum_{j=1}^{n} N_{gi}^{j}\right]^{-1} \quad (2)$$

In order to obtain the expression $\left[\sum_{i=1}^{m}\sum_{j=1}^{n} \mathrm{N}_{gi}^{j}\right]$ it is necessary to perform additional fuzzy operations with n values of the extent analysis, which is represented in Equation (3) and (4);

$$\sum_{j=1}^{n} \mathrm{N}_{gi}^{j} = \left(\sum_{j=1}^{n} \mathrm{lj}, \sum_{j=1}^{n} \mathrm{nj}, \sum_{j=1}^{n} \mathrm{uj}\right) \tag{3}$$

$$\left[\sum_{i=1}^{m}\sum_{j=1}^{n} \mathrm{N}_{gi}^{j}\right] = \left(\sum_{i=1}^{m} \mathrm{li}, \sum_{i=1}^{m} \mathrm{ni}, \sum_{i=1}^{m} \mathrm{ui}\right) \tag{4}$$

And it is required to calculate the inverse vector above by using Expression (5);

$$\left[\sum_{i=1}^{m}\sum_{j=1}^{n} \mathrm{N}_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{m} \mathrm{ui}}, \frac{1}{\sum_{i=1}^{m} \mathrm{ni}}, \frac{1}{\sum_{i=1}^{m} \mathrm{li}}\right) \tag{5}$$

Step 2: While N_1 and N_2 are triangular fuzzy numbers, the degree of possibility for $N_2 \geq N_1$ is defined as:

$$V(N_2 \geq N_1) = \sup_{y \geq x} \left(\min(\mu N_1(x), \ \mu N_2(y))\right) \tag{6}$$

It can be represented in the following manner by Expression (7):

$$V(N_2 \geq N_1) = \mathrm{hgt}(N_2 \cap N_1)\ \mu N_2(d) \tag{7}$$

$$= \begin{cases} 1, & \text{if } n_2 \geq n_1 \\ 0, & \text{if } l_1 \geq l_2 \\ \dfrac{(l_1 - u_2)}{(n_2 - u_2)(m_1 - l_1)}, & \text{otherwise} \end{cases} \tag{8}$$

Where d is the ordinate of the highest intersection point D between μN1 and μN2.

To compare μN1 and μN2, values of both, V(N2 ≥ N1) and V(N1 ≥ N2) are needed.

Step 3: The degree of possibility for a convex fuzzy number to be greater than k convex numbers Ni (i=1,2,...,k) can be defined by expression (9);

$$V(N \geq N_1, N_2, ..., N_k) = V[(N \geq N_1), (N \geq N_2), \dots, (N \geq N_k)] \quad (9)$$
$$= \min V(N \geq N_i{=}1,2,3,\dots,k$$

Assume that Expression (10) is;

$$d'(A_i) = \min V(S_i \geq S_k) \quad (10)$$

for k=1,2,...,n; k ≠ i. So the weight vector is obtained by Expression (11);

$$W' = (d'(A_1), d'(A_2), ..., d'(A_m))^T \quad (11)$$

where, Ai (i =1,2,...,n) consists of n elements.

Step 4: Through normalization, the weight vectors are reduced to Expression (12);

$$W = (d(A_1), d(A_2), ..., d(A_n))^T \quad (12)$$

where W represents an absolute number.

Fuzzy TOPSIS Method

The fuzzy TOPSIS calculation most important step is given in Equation (13), i.e. Creating the Decision Matrix; aggregated ratings are calculated by using Equation (13):

$$\tilde{V}ij = \frac{1}{2}\,[\tilde{v}_{ij}^{1} \oplus \tilde{v}_{ij}^{2} \;\; \oplus \dots \;\; \tilde{v}_{ij}^{s}\,] \quad (13)$$

where $\tilde{v}_{ij}^{s}$ is the performance rating value obtained from s-th decision maker.

The basic steps of proposed fuzzy TOPSIS method can be described as follows:

Step 1: In the first step, a panel of decision makers (DMs) who are knowledgeable about supplier selection process is established. In a group that has K decision-makers (i.e. D1, D2, ..., Dk) are responsible for ranking (yjk) of each criterion (i.e. C1, C2, …, Cn) in increasing order. Then, the aggregated fuzzy importance weight for each criterion can be described as fuzzy triangular numbers $\tilde{v}j$ = (aj, bj, cj) for k = 1, 2, …, K and j = 1, 2, …, n. The aggregated fuzzy importance weight can be determined as follows:

$$d_j = \underset{k}{min}\ \{y_{jk}\},\ b_j = \frac{1}{K}\sum_{k=1}^{K} yjk,\ c_j = \underset{k}{max}\ \{y_{jk}\} \qquad (14)$$

Then, the aggregated fuzzy importance weight for each criterion is normalized as follows:

$\tilde{v}j = (a_{j1}, b_{j2}, c_{j3})$

$$\text{where } v_{j1} = \frac{\frac{1}{dj}}{\sum_{j=1}^{n}\frac{1}{dj}},\ v_{j2} = \frac{\frac{1}{bj}}{\sum_{j=1}^{n}\frac{1}{bj}},\ v_{j3} = \frac{\frac{1}{cj}}{\sum_{j=1}^{n}\frac{1}{cj}} \qquad (15)$$

Then the normalized aggregated fuzzy importance weight matrix is constructed as $\tilde{V} = (\tilde{v}1, \tilde{v}2, \ldots, \tilde{v}n)$

Step 2: A decision matrix is formed.

$$X = \begin{bmatrix} x11 & x12 & \cdots & x1n \\ x21 & x22 & \cdots & x2n \\ \cdots & \cdots & \vdots & \cdots \\ xm1 & xm2 & \cdots & xmn \end{bmatrix} \qquad (16)$$

Step 3: After forming the decision matrix, normalization is applied. The calculation is done using equations 17 and 18.

$r_{ij} = \frac{\frac{1}{xij}}{\sqrt{\sum_{i=1}^{m}\frac{1}{xij^2}}}$ for minimization objective, where i = 1, 2, …, m and j = 1, 2, …, n (17)

$r_{ij} = \frac{xij}{\sqrt{\sum_{i=1}^{m} xij^2}}$ for maximization objective, where i = 1, 2, …, m and j = 1, 2, …, n (18)

Then, normalized decision matrix is obtained as:

$$R = \begin{bmatrix} r11 & r12 & \cdots & r1n \\ r21 & r22 & \cdots & r2n \\ \cdots & \cdots & \cdots & \cdots \\ rm1 & rm2 & \cdots & rmn \end{bmatrix} \quad (19)$$

Step 4: Considering the different weights of each criterion, the weighted normalized decision matrix is computed by multiplying the importance weight of evaluation criteria and the values in the normalized decision matrix. The weighted normalized decision matrix $\tilde{V}$ for each criterion is defined as:

$$\tilde{V} = [\tilde{V}_{ij}]_{mxn} \text{ for } i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n \quad (20)$$

Where $\tilde{V}ij = rij \text{ X } \tilde{o}j$

Here $\tilde{V}ij$ denotes normalized positive triangular fuzzy numbers.

Step 5: Then fuzzy positive ($\tilde{A}^*$) and fuzzy negative ($\tilde{A}^-$) ideal solutions are determined as follows:

$\tilde{A}^* = (\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*)$ where

$\tilde{V}_j^* = \left\{\max_i(vij1),\ \max_i(vij2), \max_i(vij3)\right\}$ and

$\tilde{A}^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-)$ where

$\tilde{V}_j^- = \left\{\min_i(vij1),\ \min_i(vij2), \min_i(vij3)\right\}$

for $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$ (21)

Step 6: Then the fuzzy distance of each alternative from fuzzy positive and fuzzy negative ideal solutions are calculated as:

$$\tilde{a}_i^* = \sqrt{\sum_{j=1}^{n}(\tilde{v}_j^* - \tilde{v}_{ij}^*)} \quad \text{and} \quad \tilde{a}_i^- = \sqrt{\sum_{j=1}^{n}(\tilde{v}_j^- - \tilde{v}_{ij}^-)}$$

$i = 1, 2, \ldots, m$ (22)

Step 7: Then the fuzzy closeness coefficient $\tilde{N}$ is determined as:

$$\tilde{N}_i = \frac{\tilde{a}_i^-}{\tilde{a}_i^* + \tilde{a}_i^-} \quad i = 1, 2, \ldots, m \quad (23)$$

The fuzzy closeness represents the distances to the fuzzy positive ideal solution and the fuzzy negative ideal solution simultaneously.

Step 8: The fuzzy closeness coefficient defuzzified as follows:

$$N_i = \sqrt[3]{N_{i1} \cdot N_{i2} \cdot N_{i3}} \quad (24)$$

Fuzzy VIKOR Method

The VIKOR method is one of the FMCDM. It was developed by Serafim Opricovic (1990) to solve decision problems with conflicting and non-commensurable criteria, assuming that compromise is acceptable for conflict resolution. VIKOR ranks alternatives and determines the compromise solution closest to the ideal solution. The international recognition of the VIKOR method was due to contribution of Serafim Opricovic and Gwo-Hshiung Tzeng (2004).

In this study Fuzzy-VIKOR method is used to solve problem in a triangular hesitant fuzzy environment. The triangular fuzzy numbers are used to handle imprecise numerical quantities. Fuzzy-VIKOR is based on the aggregating fuzzy merit that represents distance of an alternative to the ideal solution (Incekara,2020). The related steps are as follows (Incekara,2020):

Step 1: Determine the positive triangular ideal solution (PTIS) and the negative triangular ideal solution (NTIS).

$A^+ = \{f_1^+, f_2^+, \dots, f_n^+\}$ where

$f_j^+ = \bigcup_{i=1}^{m} f_{ij} = \bigcup_{\gamma 1j \in f1j \dots \gamma mj \in fmj} (\max(\gamma_{1j}^{L},\dots,\gamma_{mj}^{L}), \max(\gamma_{1j}^{M},\dots,\gamma_{mj}^{M}), \max(\gamma_{1j}^{U},\dots,\gamma_{mj}^{U}))$

$A^- = \{f_1^-, f_2^-, \dots, f_n^-\}$ where

$f_j^- = \bigcap_{i=1}^{m} fij = \bigcap_{\gamma 1j \in f1j \dots \gamma mj \in fmj} (\min(\gamma_{1j}^{L},\dots,\gamma_{mj}^{L}), \min(\gamma_{1j}^{M},\dots,\gamma_{mj}^{M}), \min(\gamma_{1j}^{U},\dots,\gamma_{mj}^{U}))$ (25)

Step 2: The aggregated fuzzy ratings of alternatives with respect to criterion are calculated by using below Sj and Rj below equations:

$$\tilde{S}_j = \sum_{j=1}^{n}[\tilde{w}_i \ (\tilde{f}_i^* - xij) / (\tilde{f}_i^* - \tilde{f}_i^-)] \tag{26}$$

$$\widetilde{R}_j = \max_i[\ \tilde{w}_i\ (\tilde{f}_i^* - xij) / (\tilde{f}_i^* - \tilde{f}_i^-)] \tag{27}$$

where wi are the weights of the criteria expressing their relative importance.

Step 3: Normalization. Compute the values $\widetilde{Q}_i$ by using below expressions:

$$\tilde{S}^* = \min_i \tilde{S}_i\ ,\ \tilde{S}^- = \max_i \tilde{S}_i \tag{28}$$

$$\widetilde{R}^* = \min_i \widetilde{R}_i\ ,\ \widetilde{R}^- = \max_i \widetilde{R}_i \tag{29}$$

$$\widetilde{Q}_i = v\frac{\tilde{S}_i - \tilde{S}^*}{(\tilde{S}^- - \tilde{S}^*)} + (1-v)\left(\widetilde{R}_i - \widetilde{R}^*\right)/(\widetilde{R}^- - \widetilde{R}^*) \tag{30}$$

Step 4: Rank the alternatives by sorting the values of S, R and Q in decreasing order which results in three ranking lists.

$$BNP_i = [(u_i - 1) + (m_i - l_i)]\ /3 + l_i \tag{31}$$

Step 5: Propose as a compromise solution the alternative A' which is ranked the best by the measure Q(minimum) if the following two conditions are satisfied:

CC1: Acceptable advantage:

$$Q\ (A'') - Q(A') \geq DQ \tag{32}$$

where A" is the alternative with second position in the ranking list by Q; DQ=1/(m-1)

DQ = 1 / (m-1) (if m≤5 ise DQ=0.25); where m is the number of alternatives.

CC2: Acceptable stability in decision: Alternative A" must also be the best ranked by S or/and R. This compromise solution is stable within a decision making process, which could be “voting by majority rule” (when $v > 0.5$ is needed) or by “consensus” $v \approx 0.5$ or with ”veto” ($v < 0.5$). Here v is the weight of the decision making strategy “the majority criteria” or (“maximum group utility”). If one of the two conditions is not satisfied, then a set ofcompromise solutions is proposed, which consists of:

- Alternatives A” and A’ if only condition CC2 is not satisfied, or

- Alternatives A’, A”… Am if condition CC1 is not satisfied, Am is determined by the relation $Q(A^m) - Q(A') \leq DQ$ for maximum m (the positions of these alternatives are “in closeness”).

In the study Fuzzy-AHP, Fuzzy-TOPSIS and Fuzzy-VIKOR procedures and related calculations have been coded/solved by using MATLAB program.

Selection of Natural Gas Tariffs Elements considering UGS systems

Natural Gas Tariffs Elements considering 7 dimensions-main UGS systems, i.e. measuring scale, consists of 7 dimensions-main criteria and 36 evaluation factors-sub-criteria. In the process of prioritization of criteria, subcriteria and alternatives, the DMs used in the selection process was consulted. A questionnaire was developed following the methodology proposed for the below methods, which was answered by 27 experts/DMs.

In the study 7 main criteria, i.e. Allowed revenue (AR) (C1), Operating and maintenance expenditures (OPEX) (C2), Gas losses (C3), Regulated asset base (RAB) and return on the RAB (C4), Depreciation (C4), Administrative provisions (amendment of tariffs, tariff methodology...) (C5), Storage fees (capacity fees, injection fees, withdrawal fees) (C6) and 36 related subcriteria are evaluated/assessed by each expert/DM. For the case of prioritization of the criteria, after the aggregation process performed with the answers of the 27 experts, the comparison matrix was obtained. The pairwise comparison matrices for subcriteria and alternatives are calculated. Subsequently, the normalized pairwise comparison matrix of criteria was obtained. The priority vector and the CR for the criteria were obtained. To obtain the other priorities, the same procedure presented for the criteria was applied. In order to facilitate the calculations; which enters the individual judgments of the experts and generates the local and global preferences of all levels of the hierarchical tree (criteria and subcriteria).

Hereunder, natural gas tariffs considering underground gas storage system's main criteria and related sub-criteria are described:

Allowed Revenue (AR):

Allowed revenue represents the maximum income that an underground gas storage (UGS) operator is permitted to recover through regulated tariffs during a defined regulatory period. It is designed to ensure full recovery of efficiently incurred costs, including capital and operational expenditures, while providing a reasonable return on investment and preventing excessive pricing due to the natural monopoly nature of UGS facilities.

Operating and Maintenance Expenditures (OPEX):

Operating and maintenance expenditures include all ongoing costs required for the safe, reliable, and efficient operation of underground gas storage facilities. These costs typically cover labor, energy consumption for compression and injection, routine maintenance of wells and surface equipment, monitoring of reservoir integrity, environmental compliance, and safety-related activities, and they are usually subject to regulatory efficiency assessments.

Gas Losses:

Gas losses refer to the volume of natural gas that is consumed, lost, or rendered unrecoverable during storage operations. In the context of UGS systems, these losses mainly arise from fuel gas used for compressors, unavoidable leakage, measurement discrepancies, and the technical requirements related to cushion gas, and they are generally recognized within tariff calculations either as physical allowances or as cost-based compensation.

Regulated Asset Base (RAB) and Return on the RAB:

The regulated asset base represents the value of the physical and intangible assets employed by the UGS operator to provide storage services, including subsurface formations, wells, compressors, and surface installations. A regulated return on the RAB is granted to compensate investors for the capital employed, typically calculated using a weighted average cost of capital that reflects the risk profile, long asset lifetimes, and capital-intensive nature of underground gas storage projects.

Depreciation:

Depreciation allows the gradual recovery of capital investments over the economic lifetime of underground gas storage assets. Given the long operational life of UGS facilities, depreciation schedules are usually extended and asset-specific, ensuring that investment costs are recovered in a stable and predictable manner while maintaining tariff continuity for storage users.

Administrative Provisions:

Administrative provisions define the regulatory framework governing tariff setting, adjustment, and revision for underground gas storage services. These provisions typically specify the tariff methodology, procedures for periodic reviews, indexation mechanisms, treatment of cost deviations, and rules for amendments, thereby ensuring transparency, regulatory certainty, and consistency with broader energy policy objectives.

Storage Fees (Capacity, Injection, and Withdrawal Fees):

Storage fees represent the practical tariff components through which allowed revenue is collected from storage users. Capacity fees are charged for reserving storage volume or deliverability, reflecting the high fixed-cost nature of UGS systems, while injection and withdrawal fees are applied to the actual use of the facility and are intended to reflect variable operational costs and system utilization.

Results

In the study 7 main criteria, i.e. Allowed revenue (AR) (C1), Operating and maintenance expenditures (OPEX) (C2), Gas losses (C3), Regulated asset base (RAB) and return on the RAB (C4), Depreciation (C4), Administrative provisions (amendment of tariffs, tariff methodology...) (C5), Storage fees (capacity fees, injection fees, withdrawal fees) (C6) and 36 related subcriteria are evaluated/assessed by each expert/DM. For the case of prioritization of the criteria, after the aggregation process performed with the answers of the 27 experts, the comparison matrix was obtained. The pairwise comparison matrices for subcriteria and alternatives are calculated. Subsequently, the normalized pairwise comparison matrix of criteria was obtained.

Natural gas tariffs elements considering UGS systems are evaluated by using Fuzzy method. After acquiring the fuzzy comparison matrices, importance weights of risk management in internal audit's dimensions; evaluation criteria is calculated by using Fuzzy method. According to the calculated criteria weights for natural gas tariffs elements' weights; the most important evaluation dimension/main-criteria is "Storage Fees", the second important evaluation dimension is "Operating and maintenance expenditures

(OPEX)" and the third important evaluation dimension is "Administrative provisions".

Conclusion

The original EU Regulation obliged EU Member States to fill their gas storage to at least 80 per cent of capacity by 1 November 2022 and to at least 90 per cent of capacity by 1 November of 2023, 2024, and 2025, known as the 'final filling target'. This requirement applied to all underground storage facilities located on their national territory and directly interconnected to a market area in their national territory.

Gas storage facilities are critical for ensuring the security of gas supply. The mandatory certification of all gas storage system operators was introduced in order to avoid potential risks resulting from non-EU-country influence over storage infrastructure. The Commission issues an opinion for each draft certification decision submitted by the certifying authorities and publishes it. After taking outmost account of the Commission's opinion, the certifying authority issues the certification decision.

EU gas supply portfolio is marked by a high import dependency, which reached nearly 84% in 2021. For some Member States, including the largest gas markets of Germany and Italy, the dependence exceeds 90%. The fall of domestic production almost by two-thirds in 2021 (up to only 17% of the total gas supply) was increasingly filled by imports. Among the key suppliers to the EU, in 2021 imports from Russia reached 34.4%, from Norway – 23.9%, from Algeria – 7.4%, and 2.5% were filled by other pipeline imports from Libya and Azerbaijan. LNG imports constituted 17.5%.

Covering around a quarter of the EU's annual gas consumption, Underground Gas Storage (UGS) is an important component in the European gas system providing security of supply and system flexibility by covering peak demand during the winter season. Storages allow commercial price absorption as well. In the context of steadily decreasing EU indigenous gas production and increasing import dependency, UGS, with other gas storage options, are becoming strategic serving as a buffer option in case of disruption.

EU's Gas Storage Regulation, formally Regulation (EU) 2022/1032, currently aims to enhance gas supply security by requiring member states to fill their underground gas storage facilities to at least 90 per cent of their capacity by 1 November each year. This regulation, adopted in June 2022, is set to expire at the end of 2025. EU member states with underground gas storage facilities are required to meet specific filling targets throughout the year, culminating in the 90 per cent target by 1 November.

On 5 March 2025 the European Commission put forward an amendment to the regulation adopted during the 2022 energy crisis. The amendment extends the application of the Gas Storage Regulation by two years (until the end of 2027). This extension had been announced as part of the Clean Industrial Deal of 26 February 2025.

A storage arrangement is understood as an obligation on a Member State without underground storage to arrange for storing gas in that of another Member State. In particular, the Regulation obliged Member States without underground storage to make sure their market participants had arrangements with storage system operators (or other market participants) in other Member States which do have underground storage. These arrangements had to provide by 1 November for the use of storage volumes equal to at least 15 per cent of the Member State's average annual consumption over the previous five years. Where the storage capacity of a Member State is larger than its annual gas consumption, a Member State without underground storage capacity which has access to it, is obliged to ensure that by 1 November each year, storage volumes must reach the level of its average use over the preceding five years or else demonstrate that corresponding capacity has been booked. In case of the latter, a Member State without underground storage capacity must provide by 1 November for the use of storage volumes at least at the level of 15 per cent of their average annual consumption over the preceding five years.

Therefore UGS plays an important role to balance the European gas system and to cover peak demand during winter. Gas storages play an important role for ensuring continuity of gas supply; it is an important source of gas flexibility during the winter and are refilled during the summer period. The role of storages becomes more relevant in a context where the EU indigenous gas production consistently declines year on year, increasing the gas import dependency from external gas producers to the EU. The UGS inventory level on 1 October 2021 is the lowest of the past 5 years, and it has continued below the average during the winter of 2021-2022. This is primarily due to a low storage level at the end of winter 2020-2021, combined with a storage injection season characterised by extremely high gas wholesale prices which did not incentivize market participants to store gas in comparison to previous years.

Over the course of 2022 EU adopted a significant amount of 'emergency' legislation to address the consequences of the energy crisis, which had been engulfing Europe since late 2021.

EU Gas Storage Regulation was set to expire on 31 December 2025. The Regulation obliged Member States to fill their storage to at least 90 per cent of capacity by 1 November 2023 (and each subsequent year) for as long as the Regulation was in force thus making the 1 November 2025 target. The Regulation also established a filling trajectory whereby EU Member States' storage was to be filled to a certain capacity by 1 February, 1 May, 1 July, and 1

September of every year the Regulation was in force (“intermediary targets”).

In EU, ACER, i.e. Agency for the Cooperation of Energy Regulators, published “Tariff Methodologies: Examples, Public Consultation on Draft Framework Guidelines on rules regarding harmonised transmission tariff structures for gas (Ref: PC_2013_G_03)” document, in the document harmonised transmission gas tariff methodologies in EU is explained in detail. The aim of this document is to illustrate the cost allocation methodologies described in the Framework Guidelines for Harmonised Tariff Structures with a simple network situation examples, and allow stakeholders taking part in the Public Consultation to better understand and comment the approach currently envisaged. In the matrix approach is used, the matrix model is a simplified version of the entry-exit matrix model, and it is based on the same assumptions of the capacity-weighted distance – variant A (CWD) model, in order to favour comparability of outcomes. Assumptions on the allowed revenue are Total Allowed revenue (€), Capacity/commodity split, revenue to be collected from capacity charges, revenue to be collected from commodity charges, Entry/Exit split percentage and revenues.

Main methodology is; defining a cost driver and applying the cost driver to network segments. When defining a cost driver (“Normalized Transport Cost-TC”), the simplified model takes into account the following features of each segment:

a) technical capacity (Mcm/day);

b) standard investment cost index in relation to capacity (IC);

c) length.

Most gas storage capacity in EU corresponds to depleted and aquifers fields, which are mainly used to store large volumes of gas to balance seasonal swings of gas demand and to the extent possible also for short-term trading and balancing. All EU but Portugal and Sweden report having depleted and/or aquifers storage sites. In addition, 8 EU member count with salt and hard rock caverns storages, representing a low but varying percentage of the total storage capacity. Caverns are primarily used to optimise gas portfolios in the short term as they typically allow for several gas injection and withdrawal cycles per year.

Gas in storage levels are subject to regular monitoring by the storage system operators (SSO), network operations and most NRAs. The majority of NRAs, despite noting that the vigilance over gas storage levels has increased, and do not report that current Gas In Storage (GIS) levels are a concern.

In the study 7 main criteria, i.e. Allowed revenue (AR) (C1), Operating and maintenance expenditures (OPEX) (C2), Gas losses (C3), Regulated asset base (RAB) and return on the RAB (C4), Depreciation (C4), Administrative provisions (amendment of tariffs, tariff methodology...) (C5), Storage fees (capacity fees, injection fees, withdrawal fees) (C6) and 36 related subcriteria are evaluated/assessed by each expert/DM. For the case of prioritization of the criteria, after the aggregation process performed with the answers of the 27 experts, the comparison matrix was obtained. The pairwise comparison matrices for subcriteria and alternatives are calculated. Subsequently, the normalized pairwise comparison matrix of criteria was obtained. The priority vector and the CR for the criteria were obtained. To obtain the other priorities, the same procedure presented for the criteria was applied. In order to facilitate the calculations; which enters the individual judgments of the experts and generates the local and global preferences of all levels of the hierarchical tree (criteria and subcriteria).

The calculated criteria weights for risk management in natural gas tariffs elements' weights; the most important evaluation dimension/main-criteria is “Storage Fees”, the second important evaluation dimension is “Operating and maintenance expenditures (OPEX)” and the third important evaluation dimension is “Administrative provisions”.

While the Storage Regulation has only been extended until the end of 2027, it is possible that it could become a permanent instrument as part of the ongoing review of the EU energy security framework. Its aim is to make the EU’s energy system “more prepared, secure and resilient to current and future crises”, and it seeks to determine how the current energy security framework should be amended for this purpose.

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CHAPTER 5

QUALITY MANAGEMENT IN TEXTILE PRODUCTION: MULTIFACETED CONTROL AND EVALUATION OF THE PRODUCTİON PROCESS

Şeyma EMEÇ[1]

Giriş

The textile industry encompasses multi stage and complex production processes that require high levels of quality control and process optimization to maintain competitive strength in the global market and to respond rapidly to market demands (Das, 2013; Vachtsevanos et al., 1994). This complex structure, combined with high production volumes, has made the management of various types of defects and nonconforming products that arise throughout the process a critical necessity for the sector (Ata et al., 2020; Muhammad et al., 2022).

The importance of quality planning in the textile industry is not limited to final product control, which is merely a reactive process; it directly affects the sustainability of the company in competitive market conditions (MUSIAD, 2025). The increasing complexity of production processes and the use of advanced

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technologies such as high speed weaving (Vachtsevanos et al., 1994) significantly increase the cost and impact of defects. Therefore, it is vital to ensure quality at the design and planning stage of the process rather than sorting out defective products after production has started. Effective quality planning minimizes process variability (Akyüz & Gören, 2024), reduces rework (repair) and scrap rates (Muhammad et al., 2022), thereby lowering operational costs and maximizing customer satisfaction. This requires the use of tools such as Statistical Process Control (SPC) not only for monitoring but also for proactively stabilizing the process in advance.

This study, prepared in this context, aims to statistically evaluate the product quality obtained in a textile production line. The study aims to examine process performance and identify possible out of control situations by utilizing real production data from different product groups. Within the scope of the application, the total production quantity, number of first-grade products, number of repaired products, and number of second grade (defective) products for 12 different product groups were analyzed. Considering the discrete (qualitative) nature of the process data and the different sample sizes, two basic qualitative control charts frequently used in the literature for such applications were applied: the number of defective parts (np) control chart and the number of defects per unit (u) control chart. These charts provide a robust foundation for monitoring and improving quality performance by keeping process variation under control on a product group basis.

Literature Review

In the textile industry, quality control has become a critical management function due to high production volumes, multi-stage process structures, and the diversity of defect types. For this reason, Statistical Process Control (SPC) has found extensive application in textile literature as a means of process variability, lower defect rates, and ensure production line stability. Within SPC, methods such as Pareto analysis, control charts, root cause analysis, and experimental design are used as fundamental tools for identifying the sources of defects and improving process performance. This section provides a comprehensive summary of the literature on SPC applications in the textile sector, based on published scientific articles.

There are numerous studies on identifying and resolving quality issues in textile processes. Vachtsevanos et al. (1994) developed a control system suitable for the dynamic structure of textile processes by integrating SPC techniques with fuzzy control approaches and revealed the effects of modeling variability on quality performance in weaving and yarn processes. The theoretical foundations of process control play a critical role in stabilizing textile quality assurance systems. Das (2013) emphasized the necessity of a statistical approach in process design by systematically establishing test methods and statistical quality control principles in textile production. Similarly, Camargo et al. (2008) made significant contributions to increasing the reliability of control charts in variation estimation by developing Bayesian process control models.

When examining studies conducted on direct production data in the textile industry, it is evident that control charts play a critical role in identifying quality problems arising in different processes. In a comprehensive analysis conducted at a denim washing facility in Turkey, Ata et al. (2020) classified quality problems using Pareto analysis and p-control charts; they determined that a significant portion of the defects were due to “chemical repair,” “blue ground,” and “chemical density.” The study also noted that the Laney-p control chart provides more reliable results in processes with excessive variability. Similarly, Öngelen and Köksal (2024), who examined defect distributions arising in a production line, used Pareto analysis and control charts together to identify critical defect types in the process and offered recommendations for improving quality performance.

Studies on process capability and performance improvement also occupy an important place in the literature. Akyüz and Gören (2024) evaluated the production process in the conductor industry using histograms, Pareto analysis, scatter diagrams, and control charts to identify the critical inputs of the process and developed solutions to improve process capability using multiple regression analysis. Similarly, Karadağ et al. (2024) optimized the process in fiber optic cable production using the Taguchi experimental design method, determined the most suitable parameter combinations, and revealed the effect of the parameters with ANOVA results. These studies show that experimental design and statistical modeling techniques provide a systematic framework for quality improvement processes in the textile industry.

Research on other processes affecting the quality of textile outputs is also available in the literature. Kaçar (2024), who examined the factors affecting embroidery quality, found that fabric type, backing selection, needle size, and pattern characteristics are determinants for embroidery quality. Studies on yarn quality indicators were addressed by Şengöz et al. (2025), who examined the historical development of yarn irregularities; it was reported that methods such as correlograms, variance length curves, spectrograms, and image analysis were used to detect yarn defects.

Evaluating the role of quality management systems in terms of industrial efficiency and sustainability, Aykol and Demirdöğen (2025) analyzed the relationship between waste management practices and resource efficiency and demonstrated that ISO 14001 certification and the reduction of raw material use in production processes increase resource efficiency. This study reveals that quality control methods are important not only for defect reduction but also in terms of sustainable production goals. In the MUSIAD report, which provides a general assessment of the textile sector and future projections, MUSIAD (2025) emphasizes that quality management and digitalization are critical for maintaining competitive strength. Finally, studies in the literature show that SPC applications are a powerful tool for evaluating the stability of production processes, revealing that np and u control charts are widely used in the textile industry. The capacity of Pareto analysis and Ishikawa diagrams to systematically classify the root causes of defects enables the identification of critical problem areas in the process. In this context, the current study adopts these approaches suggested in the literature, examines product based defect distributions using Pareto analysis, evaluates process stability through np and u control charts, and comprehensively reveals quality deviations in the textile production line from a statistical perspective.

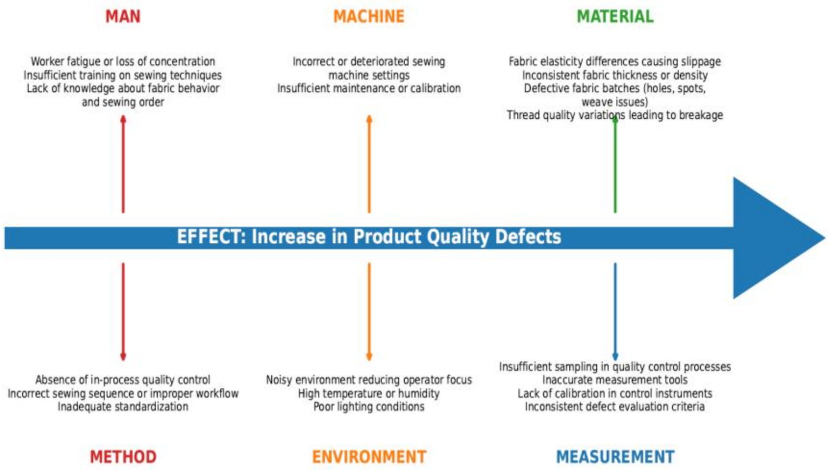
Case Study

The scope of this study is a textile company specializing in areas such as fabric production, textile design, ready to wear manufacturing, and product marketing. The company maintains a broad product portfolio covering apparel, home textiles, and industrial textile products. Thanks to its quality oriented production approach and emphasis on customer satisfaction, it has a strong and competitive position in the sector by providing production and supply services to both local and international retail chains, brands, and textile companies. The company's core process is an integrated manufacturing process that begins with the procurement of high-quality raw materials, continues with the development of original textile designs in line with customer demands and industry trends, and is implemented through processes such as cutting, pattern making, and sewing in modern production facilities. Advanced technology equipment and automation systems are used at every stage of production to increase efficiency, and quality controls throughout the process ensure that products meet specified standards.

The company's quality assurance system is supported by the integrated use of the Kaizen and Asakai methods, which are based on the philosophy of continuous improvement. Kaizen (continuous improvement) encourages small, sustainable improvements involving all employees to increase workplace productivity, reduce waste, and enhance quality, while the Asakai (morning meeting) method ensures that operational data is evaluated daily and problems encountered in the production process are identified at an early stage. These two methods enable issues affecting quality performance to be addressed in a transparent, rapid, and systematic manner.

Within this scope, a root cause analysis was performed to systematically analyze the fundamental factors that could cause quality deviations in the production process, and potential sources of defect in the process were classified using an Ishikawa (fishbone) diagram. Potential causes related to human, machine, method, material, environmental conditions, and measurement systems that affect production defects are presented in Figure 1.

Figure 1 Ishikawa Diagram Related to Defect Causes in the Production Process



In the textile industry, the high production volume, diverse types of defects, and multi stage processes have made quality control mechanisms essential. Therefore, this study aims to examine process performance and identify potential out of control situations in the process using real production data from different product groups. In practice, the total production quantity, number of first grade products, number of repaired products, and number of second grade (defective) products for 12 different product groups were analyzed. Each product group was treated as an independent sample, and np control charts and u control charts were applied to evaluate variation on a product based basis.

These two types of charts are methods commonly used in the literature to determine whether the process is under control in production environments where sample sizes differ.

Data Set and Descriptions: There are 12 different product groups analyzed within the scope of the application. The analyzed data set consists of actual quality records obtained from the production process. For each product, the total number of units produced (n), the number of first grade products, the number of repaired products, and the number of second-grade products were recorded. The total defect quantity was calculated as the sum of repaired and second grade products. These values are important as they are a direct indicator of process performance. Table 1 below shows the quality performance indicators for the products included in the application:

Table1 Quality Performance Data for Products

Product No.	Total Production (n)	Grade 1	Repair Units = n – 1G	Grade 2	Total Defect	Defect rate
A1	955	897	58	2	60	0.0628
A2	303	303	0	0	0	0.0000
A3	188	177	11	0	11	0.0585
A4	9	9	0	0	0	0.0000
A5	224	212	12	0	12	0.0536
A6	319	309	10	0	10	0.0313
A7	737	646	91	1	92	0.1248
A8	508	437	71	0	71	0.1397
A9	367	367	0	0	0	0.0000
A10	1	0	1	0	1	1.0000
A11	55	55	0	0	0	0.0000
A12	1001	960	41	2	43	0.0429

Methodology

Statistical Process Control (SPC) Methods

Theoretical Structure of the np-Control Chart

In this study, two different SPC charts were applied to evaluate quality performance:

- np-Control Chart

• u-Control Chart

The np control chart is a control chart used to monitor the total number of defective products (np) in a sample. While it is preferred especially when the sample size is fixed, it can also be applied when sample sizes vary by calculating separate control limits for each sample.

The np chart is a frequently preferred method in quality control processes as it allows for the direct monitoring of the number of defects in product groups. Its high sensitivity in detecting sudden spikes that may occur during the production process helps to reveal unexpected process failures at an early stage. Furthermore, it easily identifies quality imbalances on a product basis, clearly showing which product group is experiencing quality problems. Thanks to these features, the np chart is used as a highly effective control tool for identifying major quality deviations that arise in the process.

In this study, the number of defective products in the population is calculated as in Equation 1.

$$np_i = Total\ Defect = Repair\ Unit\ + Grade\ 2 \qquad 1$$

Control Limit Calculations

The total defect rate obtained across all product groups is calculated using Equation 2.

$$\bar{p} = \sum \frac{np_i}{n_i} \qquad 2$$

Control limits for each product group are calculated using the process average defect rate; accordingly, the center line, upper control limit, and lower control limit for the relevant product are determined using equations 3, 4, and 5, respectively: (If LCL is less than 0, it is taken as 0.)

$$CL_i = n_i.\bar{p} \qquad 3$$

$$UCL_i = n_i.\bar{p} + 3\sqrt{n_i.\bar{p}(1-\bar{p})} \qquad 4$$

$$LCL_i = n_i.\bar{p} - 3\sqrt{n_i.\bar{p}(1-\bar{p})} \qquad 5$$

u-Theoretical Structure of the Control Chart

The u control chart is a control chart used to monitor the average number of defects per unit. Its most important advantage is that it provides a correctly normalized defect rate when sample sizes differ.

The main reason for preferring the u control chart is that sample sizes vary significantly between product groups, and this situation does not allow for a reliable evaluation with classic np charts. The u chart accurately reflects process instability, even for products with small sample sizes, revealing the true behavior of the defect rate. Furthermore, this chart type allows for the comparison of defect levels per unit across different product groups, enabling a more comprehensive and comparable assessment of process performance.

In this study, the unit defect rate is determined using Equation 6.

$$u_i = \frac{Total\ Defect}{n_i} \qquad 6$$

The average defect rate is found using Equation 7 in the u-control chart.

$$\bar{u} = \frac{\sum Total\ Defect}{\sum n_i} \qquad 7$$

Control limits for each product are calculated using equations 8, 9, and 10: (If LCL < 0, it is considered 0).

$$CL_i = \bar{u} \quad (8)$$

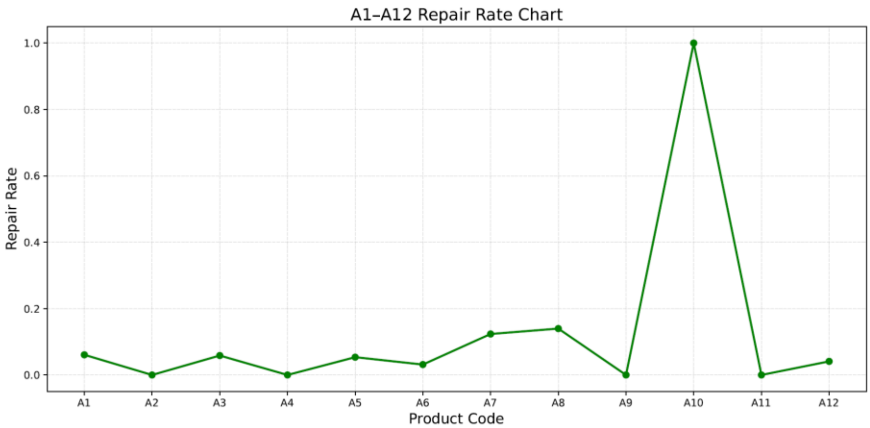
$$UCL_i = \bar{u} + 3\sqrt{\frac{\bar{u}}{n_i}} \quad (9)$$

$$LCL_i = \bar{u} - 3\sqrt{\frac{\bar{u}}{n_i}} \quad (10)$$

Research Results And Findings

This section presents, in an organized manner, the results derived from the Pareto analysis and the applications of the np and u control charts based on the production data examined in the study. Through these analyses, it became possible to investigate several aspects of process behavior, including how defects are distributed among product groups, the extent of variation within the system, and whether quality performance remains statistically stable. The Pareto analysis highlighted the product groups in which defects were concentrated, pointing to primary areas requiring improvement. The np control chart supported this evaluation by showing changes in the number of defective items across product groups and helped to identify points at which the process may have shifted from its expected pattern. The u chart, which evaluates defects on a per-unit basis, provided a clearer picture of how the process aligns with its control limits by normalizing defect levels. When these three analytical tools are used together, they offer a more complete and scientifically grounded understanding of the main factors influencing quality throughout the production process.

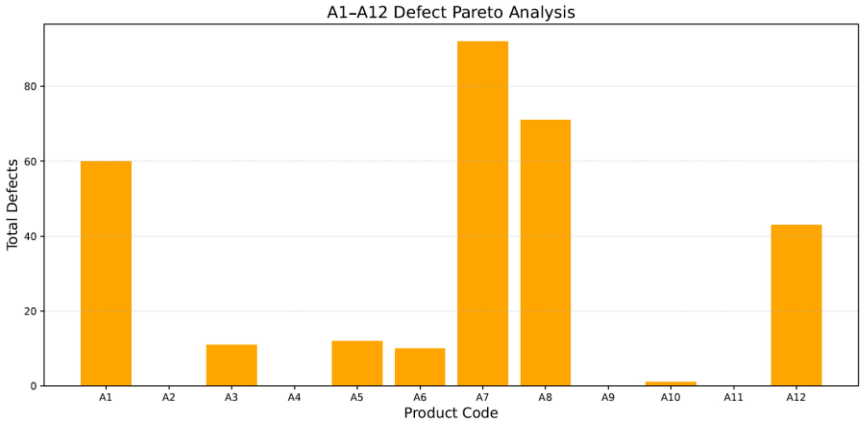
Figure 2 Repair Rate Chart for Product Groups



The distribution of repair rates by product is shown in Figure 2, revealing that the need for repairs is quite low in the vast majority of product groups, with rates approaching zero for many products. This indicates that an acceptable level of quality is maintained throughout the production process. However, it is noteworthy that repair rates are significantly higher for products A7 and A8, indicating that process variations are more pronounced for these products. The most striking finding is that the repair rate for product A10 is 100%; the fact that every single unit produced for this product requires complete repair indicates a serious process problem specific to this product type. When the graph is evaluated overall, it can be said that repair rates vary significantly by product and that the high values observed in some products suggest systematic problems at certain points in the process.

This variation in repair rates between products necessitates a Pareto analysis to see more clearly identify the products the total defect distribution is concentrated.

Figure 3 Pareto Defect Analysis for Product Groups



The distribution of defects by product has been evaluated using the Pareto analysis presented in Figure 3, which shows that the total defects are not evenly distributed among product groups and are concentrated in certain products. When examining the total number of defects, it is seen that 92 defects occurred in product A7, 71 in product A8, 60 in product A1, and 43 in product A12. The cumulative total of these four products is 266 defects, constituting a significant portion of all defects that occurred during the period under review. When the composite percentage is calculated on a product basis, it is determined that A7 and A8 together account for approximately 54% of total defects, with the addition of A1 this ratio reaches 74%, and with the inclusion of A12, it reaches approximately 89% of total defects. Thus, it can be seen that just four product groups constitute the majority of defect sources on the production line and that process variation is concentrated in these products. In contrast, no defects were observed in products A2, A4, A9, and A11; while the low number of defects in products A3, A5, and A6 indicates that the process is running stably for these products.

These results indicate that improvement efforts should primarily focus on products A7, A8, A1, and A12. It is recommended that the operational steps for these products be reviewed, machine settings be standardized, the quality of materials used be investigated, and operator-related variability be reduced. It is estimated that targeted root cause analyses and process improvement activities carried out on these products will significantly reduce the total defect rate and directly contribute to the stability of overall quality performance. The total defect rate obtained across all product groups is as follows:

After determining which product groups had the highest concentration of defects using Pareto analysis, it was deemed necessary to create np and u control charts to assess whether the process was statistically under control.

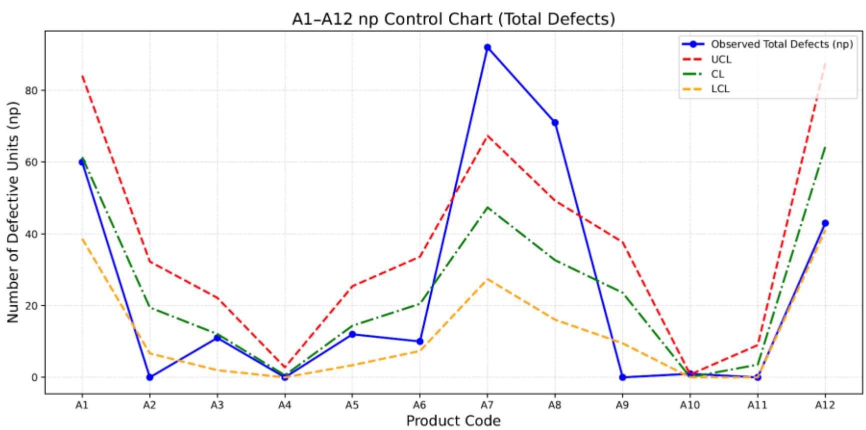
Within the scope of Section 4.1.1, the CL, UCL, and LCL values for each product group in the problem were calculated using Equations (1)–(5) used in creating the np control chart, and the results obtained are presented in Table 2.

$$\bar{p} = \frac{300}{4667} = 0.0642811227769445$$

Table 2 CL, UCL, and LCL values for each product group for the np graph

Product No.	**Total Production (n)**	**Total Defect**	**CL=$n_i.\overline{p}$**	**UCL**	**LCL**
A1	955	60	61.388472	84.125692	38.651252
A2	303	0	19.477180	32.284463	6.669898
A3	188	11	12.084851	22.173072	1.996630
A4	9	0	0.578530	2.785808	0.000000
A5	224	12	14.398972	25.410806	3.387137
A6	319	10	20.505678	33.646757	7.364599
A7	737	92	47.375187	67.349389	27.400986
A8	508	71	32.654810	49.237980	16.071641
A9	367	0	23.591172	37.686290	9.496054
A10	1	1	0.064281	0.800040	0.000000
A11	55	0	3.535462	8.991998	0.000000
A12	1001	43	64.345404	87.623782	41.067026

Figure 4 np Control Chart for Product Groups (Total Number of Defective Products)



The behavior of the total number of defective units in product groups within the process, as examined in the np control chart shown in Figure 4, reveals that the number of defects observed in a significant portion of the product groups remains within the control limits and that the process is generally statistically acceptable. However, the fact that the defect counts for products A7 and A8 are clearly above the center line indicates that process variation is higher for these products and that there may be special cause deviations in the relevant operational steps. The fact that products A1 and A12 also produce values close to the control limits suggests that these products pose a potential risk in terms of the process. On the other hand, the absence of defectsin products A2, A4, A9, and A11 indicates that both operational stability and quality performance are maintained at a high level for these products. The overall picture reveals that the process does not exhibit the same behavior across all product groups and that specific causes affecting process control, particularly in products with high defect rates, need to be examined in detail.

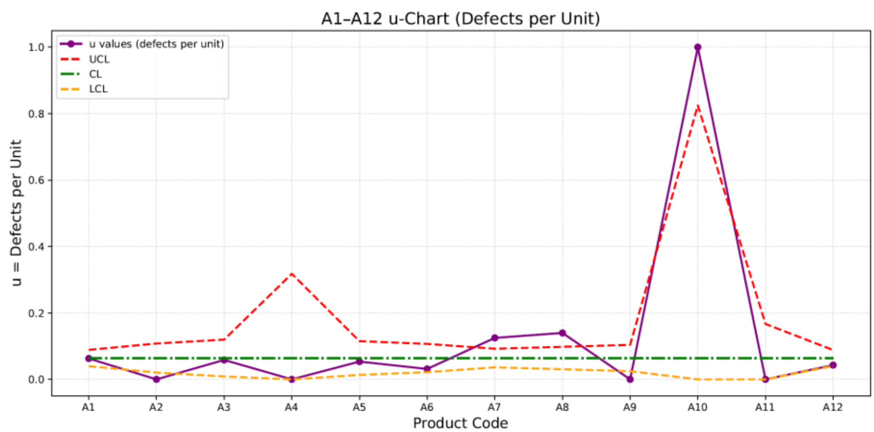
Based on Equations (6)–(10) used in calculating the u control chart in Section 4.1.2, the CL, UCL, and LCL values for each product group were determined, and the results are shown in Table 3.

$$\bar{u} = \frac{300}{4667} = 0.0642811227769445$$

Table 3 CL, UCL, and LCL values for each product group for the np graph

Product No.	Total Production (n)	Total Defects	CL=$\bar{u}$	UCL	LCL
A1	955	60	0.064281	0.088894	0.039668
A2	303	0	0.064281	0.107977	0.020585
A3	188	11	0.064281	0.119754	0.008808
A4	9	0	0.064281	0.317818	0.000000
A5	224	12	0.064281	0.115102	0.013461
A6	319	10	0.064281	0.106867	0.021695
A7	737	92	0.064281	0.092299	0.036264
A8	508	71	0.064281	0.098028	0.030534
A9	367	0	0.064281	0.103985	0.024578
A10	1	1	0.064281	0.824893	0.000000
A11	55	0	0.064281	0.166842	0.000000
A12	1001	43	0.064281	0.088322	0.04024

Figure 5 u Control Chart for Product Groups (Number of Defects per Unit)



When examining the u control chart presented in Figure 5, it is observed that the number of defects per unit remains within the control limits for the vast majority of product groups and that process variation generally exhibits a stable structure. For most products, the u values are quite close to the center line, indicating that the defect frequency is low and under control for most products. However, the u value for product A10 exceeds the upper control limit, showing an excessive spike, which clearly indicates an unusual process deviation specific to this product. The relatively high u values observed in products A7 and A8 also suggest that process variability in these products is greater than in other products.

Overall analyses reveal that quality performance varies significantly between product groups and that defects are particularly concentrated in certain products. Pareto analysis shows that the majority of defects are concentrated in products A7, A8, A1, and A12; the repair rate graph confirms that process variation in these products is higher than in other products. The np control chart shows that the number of defects in the same products approached or exceeded the control limits, while the u control chart showed that the defect rate per unit rose to an unusual level, particularly in the A10 product. When all these findings are evaluated together, it is understood that the production process is generally operating at an acceptable level, but quality issues persisting in certain product groups due to specific causes; it is seen that in depth analyses of these products are critical for improving process stability.

Conclusion

This study aimed to evaluate quality performance in a production line within the textile industry using the Statistical Process Control (SPC) approach and analyzed process behavior based on qualitative defect data. In multi stage, high volume textile production environments with various defect types, it is emphasized that traditional final product inspection alone is insufficient; in process statistical monitoring and root cause analysis are critical for comprehensive quality assurance. In this context, within a quality management system supported by continuous improvement approaches such as Kaizen and Asakai, Pareto analysis, Ishikawa diagrams, and np and u control charts were used together to reveal both the structural components of defect sources and the statistical status of process performance. The study is significant in that it demonstrates how SPC tools, which are often discussed in the literature using theoretical examples, can be integrated into a textile-specific application using real production data.

The findings revealed that quality performance was not homogeneous across product groups and that defects were concentrated in specific products. Pareto analysis showed that products A7, A8, A1, and A12 accounted for approximately 89% of the total 300 defects; this confirmed that quality losses on the production line were concentrated in a limited number of critical product groups and that the Pareto principle applied to this process. The repair rate graph revealed that process variations were higher in A7 and A8 products compared to other products, while the repair rate reaching 100% in the A10 product indicated an unusual situation in the process. The np control chart showed that the number of defective products was largely within the control limits, but values significantly above the center line were observed for products A7 and A8, while products A1 and A12 showed a risk level approaching the control limits. The u control chart revealed that the process was generally stable in terms of defect rates per unit, but that the A10 product exceeded the upper control limit, exhibiting statistically out-of-control behavior. These results show that the process operated at an acceptable level overall, but that deviations due to specific causes persisted in certain product groups.

One of the most significant contributions of this study is that it presents an applied framework based on the combined use of np and u control charts for evaluating qualitative data with variable sample sizes in the textile industry. The simultaneous analysis of the np chart, which tracks the total number of defects per product, and the u chart, which considers the defect rate per unit, enables a more accurate interpretation of process behavior in both high volume product groups and products with small sample sizes. Furthermore, through the integration of Pareto analysis and Ishikawa diagrams, not only are the products with concentrated defects identified, but the potential root causes of these defects (in terms of human, machine, method, material, environment, and measurement system dimensions) are also systematically revealed. Thus, the study provides a statistically and administratively applicable roadmap for quality improvement projects in textile businesses; it offers business managers a practical approach to determine improvement priorities based on data.

However, the study also has certain limitations, and these limitations offer new avenues for future research. First, the analyses are limited to data obtained from 12 product groups belonging to a single company and a specific period; studies conducted on different periods, different textile companies, or broader product portfolios would strengthen the generalizability of the findings. Furthermore, np and u control charts were used in this study to monitor process performance; however, the relationships between process variability and machine settings, environmental conditions, or operator variables were not explored in depth using regression, multivariate statistical methods, or experimental design (Taguchi, etc.). In future studies, the integration of process capability analyses, multiple regression models, Taguchi experimental designs, or artificial intelligence/machine learning-based early warning systems alongside control charts will provide quality management applications in the textile industry with both stronger predictive capabilities and more comprehensive solution proposals in terms of process optimization.

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CHAPTER 6

FROM DATA-DRİVEN VENTURE CAPITAL TO PERSONALIZED DECISION ENGINES: A HUMAN–MACHINE HYBRID WITH MCDM AT THE CORE

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Introduction

A growing availability of structured and unstructured information has been observed to transform the context of venture capital (VC) decision-making, yet a persistent gap has been noted between statistical accuracy and contextually grounded professional judgment; consequently, a hybrid approach has been advocated in which the strengths of human experts and machine learning (ML) systems are combined rather than pitted against each other (Mosqueira-Rey et al., 2023). Within this view, VC decisions have

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been framed as socio-technical processes in which algorithms contribute scalable pattern discovery while human agents contribute domain knowledge, contextual interpretation, and accountability.

Figure 1 shows the progression of venture capital decision-making methods. It starts with expert-only judgment, moves to data-driven analytics, then to human-in-the-loop machine learning, and finally to a personalized decision engine. Each stage represents a shift toward more structured, scalable, and technology-supported decisions. Across all stages, three key principles (governance, explainability, and performance) serve as checkpoints to ensure that the evolving decision systems remain trustworthy, transparent, and effective.

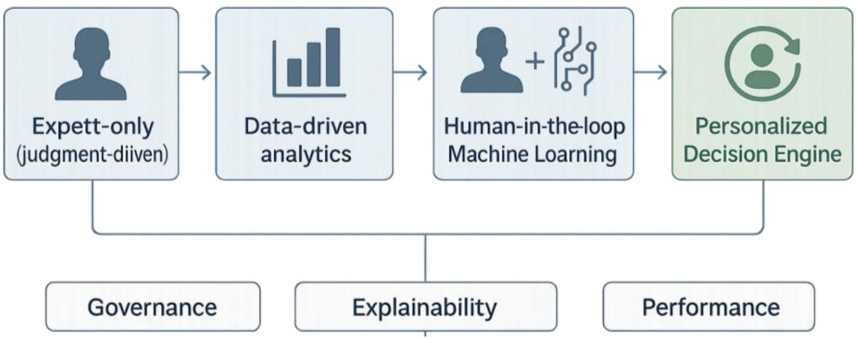

Figure 1. Evolution of venture capital decision paradigms

A range of decision-making paradigms has been outlined in Table 1, each of which is characterized by distinct inputs, strengths, limitations, and risks. Expert-only approaches are defined by qualitative judgment and tacit knowledge, though they are constrained by inconsistency and bias. Data-driven analytics are supported by repeatable metrics and dashboards, but their contextual depth is limited, and risks of metric gaming are present.

Table 1. Decision paradigms in VC and their trade-offs

Paradigm	Primary Inputs	Strengths	Limitations	Explainability	Typical Risks	Where It Excels
Expert-only (judgment-driven)	Partner experience, networks, qualitative memos	Rich context, tacit market knowledge	Inconsistency, bias, limited scalability	Narrative memos; low formal traceability	Overconfidence; selection bias	Ultra-early markets; relationship-driven deals
Data-driven analytics	Descriptive & diagnostic analytics, KPIs	Repeatability; faster screening	Shallow context; label/target mismatch	Metric dashboards; moderate	Goodhart effects; metric gaming	Mid/late-stage screening at scale
Human-in-the-loop ML (HITL)	ML scores + expert input loops	Improves accuracy under scarce/noisy data; controllability	Workflow complexity; human fatigue	Model & interaction logs; moderate-high	Confirmation bias in feedback	Domains with scarce/imbalanced data
Hybrid MCDM+ML (bridge layer)	Expert weights + criterion-level ML estimates	Explicit trade-offs; auditable ranking; robustness via sensitivity	Requires elicitation and governance	Criteria/weights/sensitivity plots; high	Weight drift; misuse of weights	IC preparation; multi-objective triage
Personalized decision engine	Global ranking + preference learning + constraints	Investor-aligned; transparent "why this"	Cold-start; fairness & policy constraints	Global+local explanations; high	Exposure imbalance; suitability breaches	LP/wealth platforms; large VC franchises

Human-in-the-loop machine learning is enhanced by expert input, which increases accuracy under noisy or scarce data, although workflow complexity and feedback bias are introduced. Hybrid multi-criteria decision-making combined with machine learning is strengthened by explicit trade-offs and auditable rankings, while governance requirements and weight drift are recognized as challenges. Finally, personalized decision engines are designed to align global rankings with investor preferences, and although transparency is emphasized, risks such as cold starts, fairness issues, and suitability breaches are acknowledged (Kellekci, 2002).

It has been emphasized that explanations and auditability are preconditions for adoption in high-stakes financial settings; therefore, explainable artificial intelligence (XAI) has been proposed as a design principle for decision support, with empirical evidence suggesting that transparent models and justification artifacts improve user trust and appropriate reliance (Coussement et al., 2024; Kostopoulos, Davrazos, & Kotsiantis, 2024). In this perspective, the objective has been to move beyond raw accuracy toward systems that are understandable, governable, and alignable with human oversight.

Against this backdrop, multi-criteria decision-making (MCDM) methods have been positioned as a suitable bridge layer, because expert value judgments (weights and trade-offs) can be separated from empirical estimates (criterion-level scores) supplied by ML; in recent work, such coupling has been associated with improvements in both interpretability and decision quality (Martyn & Kadziński, 2023; Reyes-Norambuena, Bascuñán-Ortiz, & Sauma, 2024). A coherent pathway has thus been proposed: hybrid human–machine decision framing → MCDM structuring → two-way integration with ML → investor-level personalization and governance (Hüllermeier & Słowiński, 2024a; 2024b).

The contribution of this chapter has been designed with three aims. First, a principled role for MCDM is articulated in human–machine hybrid decision systems for VC. Second, a bidirectional integration pattern with ML is presented, in which MCDM outputs guide feature/label engineering while ML methods learn or adapt MCDM parameters from outcomes. Third, a downstream transition to investor-level personalization is developed, so that general investment rankings are transformed into constrained, preference-aware recommendations.

Venture Capital Investment and Startup Success

Early-stage investing has been characterized by structural uncertainty, non-stationarity, and data sparsity; even experienced investors have been reported to operate with noisy signals where long-run outcomes are difficult to forecast ex-ante (Gompers, Gornall, Kaplan, & Strebulaev, 2020). Under such conditions, it has been found that multiple notions of value coexist, and that investment decisions require a careful expression of priorities and constraints across several dimensions.

Because outcomes and objectives vary by stakeholder, the notion of startup success has been treated as multi-dimensional and context-dependent; the choice of a success definition has been shown to affect how labels are constructed for ML tasks and what objectives are optimized in MCDM models (Cinelli, Kadziński, Gonzalez, & Słowiński, 2020). For this reason, heterogeneous definitions, ranging from exits (IPO/M&A) and financing milestones to performance measures such as return on investment (ROI), have been adopted in practice.

A practical approach has been to anchor the feature space in observable signals (organizational, technological, market, governance, and network cues) that proxy for latent success factors; such signals have been cataloged in the VC literature and can be mapped to decision criteria to support structured analysis. The taxonomy of signals is used in this chapter as the canonical dictionary that links raw data to criteria and ultimately to success objectives in Table 2.

Table 2. Taxonomy of signals able to predict the likelihood of success of a startup

Signal Family	Example Variables	Impact on Success	Typical Data Source	Example Measurement
Innovation & IP	Patent count/quality, citations	Defensibility, valuation	Patent DBs (USPTO/EPO), Lens.org	Claims-weighted patent score
Team & Leadership	Founder experience, serial exits, education	Execution probability	LinkedIn/CVs, press	Founders' weighted experience index
Investor Reputation & Syndicate	Tier of lead investor, co-investor network	Follow-on funding, exits	Crunchbase/PitchBook	Lead-investor prestige score
Market Traction	Revenue growth, user metrics, retention	Survival & fund-raising	Product analytics, revenue reports	N-month revenue CAGR; retention
Alliances & Network	Strategic partnerships, ecosystem centrality	Market access, resilience	News/APIs, KG graphs	Graph centrality (e.g., PageRank)
Financial Structure	Runway, debt mix, burn	Non-linear; excessive debt risk	Financials; filings	Months of runway; debt-to-equity
Governance & Board	Independent board seats, controls	Monitoring; Agency risk	Company page, filings	Governance scorecard
Visibility & Signaling	Media mentions, awards, brand	Attention, funding chance	Web/news/social	Normalized media index
Diversity & Inclusion	Gender/cultural diversity, equity	Mixed: creativity & resilience	HR/ESG disclosures	Diversity composite

Signal Family	Example Variables	Impact on Success	Typical Data Source	Example Measurement
Geography & Ecosystem	Hub proximity, accelerator alumni	Access to capital & talent	Geo data; accelerator lists	Ecosystem proximity index

Parallel to the signal dictionary, multiple success definitions have been observed in the literature, ranging from financing thresholds and exits to profitability and growth. The startup success is therefore adopted as a standardized label set for modeling and evaluation, and it has been emphasized that model performance should be reported separately for each definition in Table 3.

Table 3. Definitions of Startup Success

Success Definition	Operationalization	Use in Modeling/Decision
IPO	Public listing within T years of first round	Binary label; long-horizon success
M&A	Acquisition within T years	Binary label; exit success
Follow-on Funding	Achieves Series A/B (or ≥X rounds)	Survival/growth label
ROI / Value Uplift	Investor IRR ≥ threshold; valuation ↑ ≥Y×	Decision objective; continuous
Revenue Scale	Revenue ≥ R by year N; CAGR ≥ c%	Performance label/objective
Profitability	Positive EBITDA/FCF for ≥ M periods	Quality/sustainability objective
Survival	Active ≥ 5 years post-founding	Robustness label
Unicorn	Post-money valuation ≥ $1B	High-impact objective
PMF Proxy	Retention ≥ r%; NPS ≥ n; churn ≤ χ	Early traction label

A data-flow view has been found to be useful for implementation: raw sources (patents, alliances, founder/team CVs, investor brand, web mentions, capitalization) are transformed into engineered features grouped by criteria (innovation, team quality, traction, governance, network centrality), which in turn supply labels/objectives consistent with selected success definitions. This mapping is shown to enable cross-functional communication during design reviews and to support auditable decision-making artifacts.

Figure 2 illustrates how signals such as innovation, leadership, market traction, governance, and networks are translated into criteria, which then connect to different success definitions like IPO, M&A, ROI, survival, and growth. The mapping shows that each signal can influence multiple criteria, and criteria can be linked to several definitions, highlighting a many-to-many relationship. Measurement scales, such as percentages, index scores, and binary labels, are used along the process to standardize and quantify the evaluation, ensuring traceability from raw data to success outcomes.

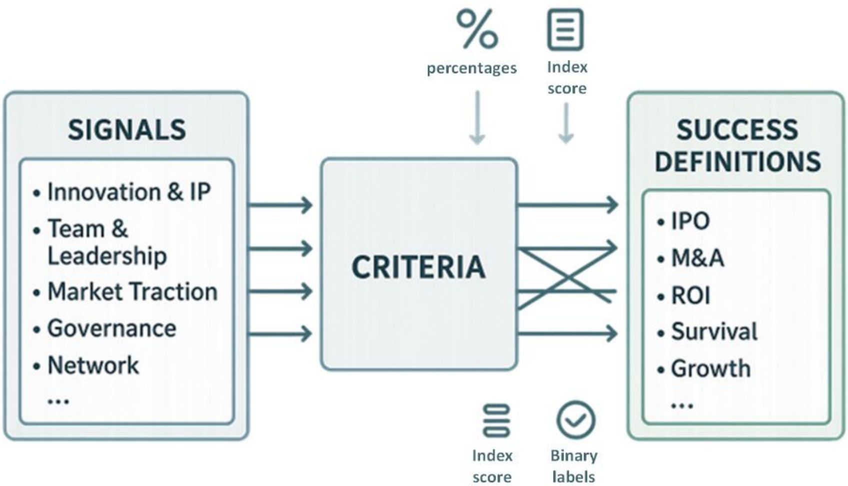

Figure 2. From signals to success criteria

Human–Machine Hybrid Decision Models in Venture Capital

Hybrid decision models have been defined as engineered collaborations in which perception, inference, judgment, and action are explicitly partitioned between humans and AI systems; human-in-the-loop (HITL) patterns have been found to be particularly beneficial when domain knowledge is tacit, data are scarce or skewed, or accountability requires reversibility and traceability (Mosqueira-Rey et al., 2023). Within VC, this perspective has been operationalized by allocating complementary responsibilities to expert investors and model pipelines.

Along the VC life cycle, hybridization has been located at four recurring touchpoints. At the sourcing stage, weak opportunities are triaged and watchlists are maintained with algorithmic assistance. At the screening stage, candidates are prioritized for due diligence by combining expert priors with model scores. At signing, term sheets and valuations have been shown to reflect value judgments that are made explicit. During supporting, post-investment actions are triaged and monitored with data-informed alerts (Gompers et al., 2020; Coussement et al., 2024).

Explainability has been characterized as adoption prerequisites in finance; mechanisms that expose why and how decisions were reached have therefore been recommended, including model cards, reason codes, and sensitivity analyses in which decision makers can inspect counterfactual scenarios (Kostopoulos et al., 2024). It has been suggested that such mechanisms help reconciliation across the investment committee and facilitate consistent documentation.

Figure 3 presents the 4S framework in venture capital decision-making: Sourcing, Screening, Signing, and Supporting. Each quadrant combines two complementary elements: a Human ring that contributes priors and constraints and a Machine Learning (ML) ring that generates scores and flags. These dual inputs from both humans and ML converge into a central hub labeled MCDM, which integrates and balances them. The diagram highlights how human expertise and machine intelligence interact at every stage of the investment cycle, with MCDM ensuring structured, auditable, and explainable decisions.

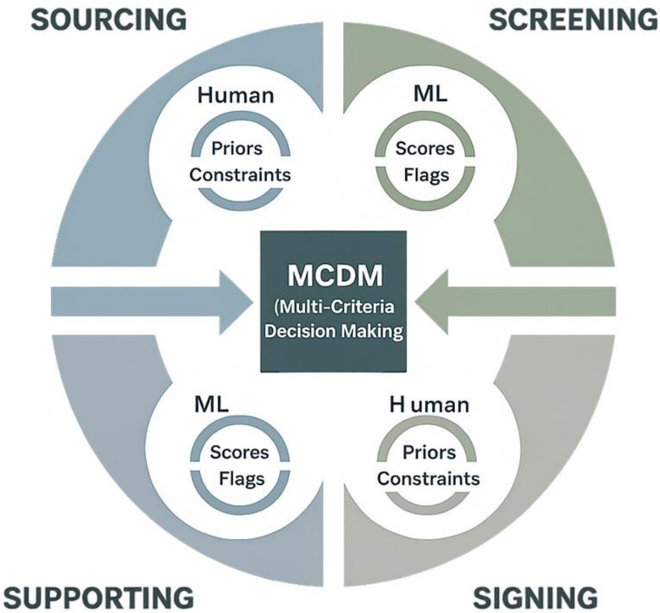

Figure 3. 4S in Human vs. Machine Learning

A bridge layer has therefore been deemed necessary to merge human judgments and model output into auditable investment priorities. MCDM has been proposed for this purpose because it exposes value trade-offs, collects heterogeneous evidence in a principled way, and returns a traceable ranking that can be interrogated through sensitivity analysis (Cinelli et al., 2020). The next section introduces this bridge and details its inputs, operations, and outputs.

In this framework, in Table 4, distinct stakeholder roles are described in terms of their inputs, methods, outputs, and evidence artifacts. Partners and investment committees are provided with priors, theses, and constraints, and their judgments are applied through weighting and reviews, resulting in documented criteria and decisions that are recorded in weight ledgers and rationale notes. Data science teams are supplied with features, models, and validation sets, and estimators and calibration techniques are employed to produce criterion scores and uncertainty measures, which are explained through model cards and validation reports. Risk and compliance functions are guided by policy rules and are implemented through rule engines and solvers, with constraint sets and overrides being documented in policy logs and exceptions files. Portfolio operations are supported by post-deal performance indicators, and monitoring dashboards are used to generate operating signals and alerts, which are evidenced in operational memos and KPI snapshots. Finally, legal and investor relations teams are informed by terms, covenants, and guidelines, and document management systems are applied to produce term sheets and disclosures, with full traceability ensured by changing control records.

Table 4. Roles and artifacts

Stakeholder	Inputs	Methods/Tools	Outputs	Evidence / Explainability Artifact
Partners/ Investment Committee (IC)	Priors, thesis, constraints	AHP weighting; reviews	Criteria weights; go/no-go notes	Weight ledger; rationale notes
Data Science	Features, models, validation	ML estimators; LTR; calibration	Criterion scores; uncertainty	Model cards; CV/holdout reports
Risk & Compliance	Policy rules (suitability, caps)	Rule engines; constraint solvers	Constraint set; overrides	Policy log; exceptions file
Portfolio Operations	Post-deal KPIs, milestones	Monitoring dashboards	Operating signals; alerts	Operational memos; KPI snapshots
Legal/ Investor Relations	Terms, covenants,	Document management; audit trail	Term sheets; disclosures	Change-control records

Stakeholder	Inputs	Methods/Tools	Outputs	Evidence / Explainability Artifact
	LP guidelines			

AHP: Analytic Hierarchy Process, CV: Cross-Validation, IR: Investor Relations, LTR: Learning to Rank, LP: Limited Partner

Multi-Criteria Decision-Making (MCDM) as the Bridge

Signals have been mapped to decision criteria through a documented schema in order to enable various MCDM techniques to be applied while acknowledging scale heterogeneity and uncertainty (Cinelli et al., 2020). The signal-to-criterion mapping has been observed to simplify traceability from raw data to decision rationale.

Weight elicitation has been handled by expert-driven approaches (AHP, FAHP) as well as data-driven schemes that infer weights from revealed preferences; robustness to missing or imprecise information has been studied within Stochastic Multi-Criteria Acceptability Analysis (SMAA), which samples feasible weight spaces and reports acceptability indices, an approach that has been recommended when value judgments are uncertain or contested (Pelissari, Oliveira, Ben Amor, Kandakoglu, & Helleno, 2020). Practical governance has been aided by a change-control process for weight updates.

The bridge role becomes concrete when experts provide weights (value trade-offs) and ML systems provide criterion-level estimates (scores with uncertainty); MCDM normalizes and aggregates these inputs into an auditable ranking, where each recommendation can be accompanied by a contribution breakdown and by sensitivity plots that show rank stability under weight perturbations (Reyes-Norambuena et al., 2024). Such artifacts have been linked to higher trust in human–AI collaboration.

When data are scarce or noisy, as in early-stage ventures, fuzzy extensions and interval judgments have been used to stabilize results; spherical-fuzzy and related approaches have been reported to preserve decision quality under incomplete information while maintaining group-decision traceability (Ayyildiz & Taskin Gumus, 2022). These techniques have been recommended when criteria are difficult to measure directly or when proxies must be used.

Figure 4 illustrates the concept of two shores connected by an MCDM bridge. On one side, the Human Value Model represents expert inputs such as weights, trade-offs, and priors. On the opposite side, ML Criterion Estimators provide data-driven scores with associated uncertainty. The MCDM bridge connects these two perspectives by applying processes like Normalization, Aggregation, and Dominance, ensuring structured integration. Beneath the bridge, a Traceability Ledger highlights accountability and auditability, reinforcing transparency in decision-making between human judgment and machine learning outputs.

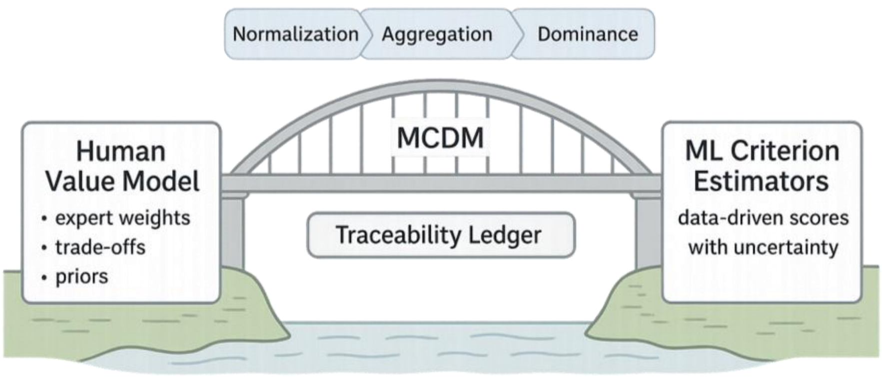

Figure 4. Two Shores: Human value model vs. ML criterion estimators

In Table 5, a variety of signals have been structured as decision criteria, and their measurement, normalization, and weighting approaches have been specified. Patent quality and citations have been normalized using Z-scores and capped, with weights assigned through the AHP and Fuzzy Analytic Hierarchy Process FAHP, based on data from patent databases, while field normalization has been recommended. Founder serial success has been mapped from ordinal to interval scales, with weights derived through AHP and SMAA, using CV records and LinkedIn data, though survivorship bias has been noted. Lead investor tier has been expressed on a 0–1 scale and weighted via AHP or SMAA, with Crunchbase used as a source, but vintage effects have been recognized. Strategic alliances have been measured with graph centrality and weighted through Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE) or Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), based on news and knowledge graphs, with adjustments for partner quality. Debt and runway have been expressed in months or debt-equity ratios and weighted through *Data Envelopment Analysis (DEA)* and AHP, using financial data, with non-linear risk penalties applied. User retention has been measured as a percentage and weighted with TOPSIS from analytics sources, with seasonality adjustments considered. Media mentions have been log-scaled, weighted with AHP, and sourced from web and news databases, though duplication controls have been required. Board independence has been expressed as a percentage of independent members, weighted by AHP using filing data, and subject to jurisdictional variation. Team diversity has been captured through composite indices, weighted by FAHP from HR and ESG sources, with sensitivity to protected attributes emphasized. Accelerator alumni status has been recorded as binary with cohort rank, weighted by AHP from accelerator datasets, with recognition of confounding selection effects.

Table 5. Signals, Decision Criteria, and Weighting in MCDM

Signal	Decision Criterion	Scale / Normalization	Weighting in MCDM	Example Data Source	Notes
Patent quality/citations	Innovation & Defensibility	Z-score; capped	AHP / FAHP	Patent DBs	Consider field-normalization
Founder serial success	Team Quality	Ordinal → interval mapping	AHP / SMAA	CV/LinkedIn	Guard for survivorship bias
Lead investor tier	Signaling & Syndication	0–1 (tiered)	AHP / SMAA	Crunchbase	Beware vintage effects
Strategic alliances	Ecosystem Access	Graph centrality	PROMETHEE / TOPSIS	News/KG	Weight by partner quality
Debt/runway	Financial Resilience	Months; D/E ratio	DEA / AHP	Financials	Non-linear risk penalty
User retention	Traction & PMF	% retention	TOPSIS	Analytics	Seasonality adjustments
Media mentions	Visibility	Log-scaled	AHP	Web/news	De-duplication needed
Board independence	Governance	% independent	AHP	Filings	Jurisdictional differences
Team diversity	Human Capital Diversity	Composite index	FAHP	HR/ESG	Sensitive attributes care
Accelerator alumni	Ecosystem Quality	Binary + cohort rank	AHP	Accelerator data	Confounding by selection

Integration of MCDM and Machine Learning

A two-way coupling has been documented between MCDM and ML. In the MCDM→ML direction, criterion weights have been used for feature weighting or selection, composite MCDM scores have been used as weak labels for learning-to-rank, and sensitivity analyses have guided feature engineering. In the ML→MCDM direction, historical decisions and outcomes have been used to learn or adapt MCDM parameters (weights, thresholds) via preference learning and disaggregation (Martyn & Kadziński, 2023; Hüllermeier & Słowiński, 2024a, 2024b; Reyes-Norambuena et al., 2024).

Early integrated frameworks demonstrated that predictive models could populate criterion-level estimates that are then aggregated by MCDM, with reported gains in both accuracy and interpretability (Kartal, Oztekin, Gunasekaran, & Cebi, 2016). More recent work in supply chains has shown that hybrid MCDM+ML can be made explainable by keeping MCDM at the heart of the process and using interpretable ML components—an approach that has been argued to be transferable to VC settings (Abdulla & Baryannis, 2024).

Validation regimes have combined statistical metrics (AUC, PR-AUC, NDCG/MAP) with decision metrics (hit rate, time-to-IC decision, adverse-selection delta), while sensitivity analyses disclose rank volatility under weight shifts; recommendations have included consistent cross-validation designs and shift detection to maintain calibration over time (Coussement et al., 2024; Reyes-Norambuena et al., 2024). In addition, it has been advised that documentation artifacts be maintained as part of model risk management.

Figure 5 shows a cyclical feedback loop that integrates human and machine learning inputs for decision-making. It begins with Criteria Discovery, followed by ML Estimators, which generate predictive insights. These feed into MCDM Aggregation & Ranking, where multi-criteria methods organize and prioritize options. The process continues with Observed Outcomes & Expert Feedback, which evaluates real-world performance and refine assumptions. Finally, the cycle loops back through Weight and Model Updates (implicit in the flow), ensuring continuous improvement. Alongside the loop, Documentation Artifacts, such as model cards, rationale notes, and sensitivity plots, provide transparency, accountability, and auditability throughout the process.

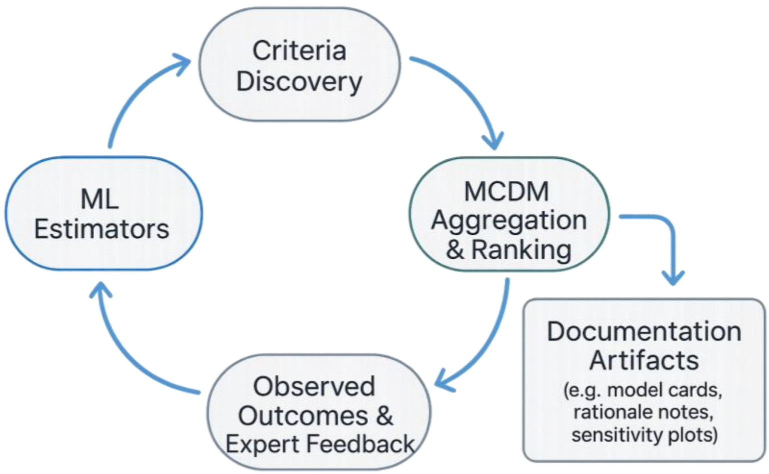

Figure 5. Closed Feedback Loop in Hybrid Decision-Making

In Table 6, the comparative characteristics of pure ML, pure MCDM, and hybrid MCDM+ML approaches have been outlined across key dimensions. Interpretability is considered low to medium in pure ML, where XAI techniques are required, while pure MCDM and hybrid methods provide high transparency through explicit weights, criteria, and combined global-local explanations. Accuracy under sparse or noisy data is limited to medium levels in both pure ML and pure MCDM, whereas hybrid approaches achieve high accuracy by leveraging HITL inputs and prior knowledge.

Robustness to data drift is only moderate in pure ML, higher in MCDM due to sensitivity analysis, and strongest in hybrid methods through dual monitoring mechanisms. Governance and auditability are rated as medium for ML but high for both MCDM and hybrid designs, reflecting the traceability of weights and decision processes. Data requirements are high in ML, low to medium in MCDM, and moderate in hybrid systems. Scalability is maximized in ML and hybrid approaches but remains medium in pure MCDM. Human effort is moderate in ML, high in MCDM due to weight elicitation, and moderate in hybrid systems where workload is shared. Typical applications are aligned with these characteristics: pure ML excels in large and stable datasets, pure MCDM is applied to low-data, value-heavy contexts, and hybrid MCDM+ML is recommended for complex and regulated decision-making environments.

Table 6. Pure ML vs. Pure MCDM vs. Hybrid

Dimension	Pure ML	Pure MCDM	Hybrid MCDM+ML
Interpretability	Low–Medium (XAI needed)	High (weights/criteria)	High (global+local)
Accuracy under sparse/noisy data	Medium	Medium	High (HITL + priors)
Robustness to drift	Medium (needs monitoring)	Medium–High (sensitivity)	High (dual monitoring)
Governance / Auditability	Medium	High	High
Data Requirements	High	Low–Medium	Medium
Scalability	High	Medium	High
Human Effort	Medium	High (elicitation)	Medium
Typical Use	Large, stable datasets	Low-data, value-heavy	Complex, regulated decisions

From General Priority Lists to Personalized Decision Engines

A hybrid MCDM+ML pipeline has typically been shown to yield an investor-agnostic global ranking, which is useful for portfolio-level triage but misaligned with heterogeneous investor goals; this limitation has motivated the use of preference learning and recommender-system techniques tailored to financial services (Wu & Li, 2025). In this setting, investor profiles have been inferred from both explicit inputs and implicit interaction data under regulatory and suitability constraints.

Recent surveys have documented knowledge-graph-based recommenders and embedding methods that leverage structured side information to handle sparsity, cold start, and explainability—capabilities directly relevant when portfolio constraints and sector exposures must be respected (Zhang, Zain, Zhou, Chen, & Zhang, 2024). The adoption of such methods has been suggested to improve personalization quality under constrained reranking.

Fairness and exposure balance have been treated as first-class concerns in recommender systems; multi-stakeholder surveys have emphasized that rank exposure may need to be controlled to avoid systematic under-recommendation of certain categories, which suggests that constrained re-ranking should be embedded in financial recommendation engines (Jin, Wang, Zhang, Zheng, Ding, Xia, & Pan, 2023; Jugovac, Jannach, Lerche, & Karimi, 2023).

The bridge from a hybrid global ranking to personalization has been constructed as follows. First, a global priority list is created by the hybrid pipeline, making the role of criteria and weights transparent. Second, investor preferences are learned from explicit and implicit signals using supervised, contextual bandit, or Bayesian preference models under appropriate governance. Third, the global list is filtered and re-weighted by the investor profile while respecting policy constraints (suitability, concentration, liquidity), and recommendations are generated with rationales that reference back to MCDM criteria (Wu & Li, 2025; Zhang et al., 2024).

Figure 6 depicts an end-to-end decision pipeline that integrates signals and machine learning with preference-aware re-ranking. It begins with Signals / Labels, which are processed by ML Estimators to generate predictive insights. These outputs feed into Preference Learning (Profiles + Constraints), which adapts decisions to individual investor needs. The system then applies Personalized, Constrained Re-Ranking to ensure alignment with policy and suitability requirements. Finally, the Presentation Layer with Rationale Cards communicates recommendations in a transparent and explainable manner. Feedback arrows link back to the MCDM Weight Ledger and preference models, ensuring continuous adaptation and governance.

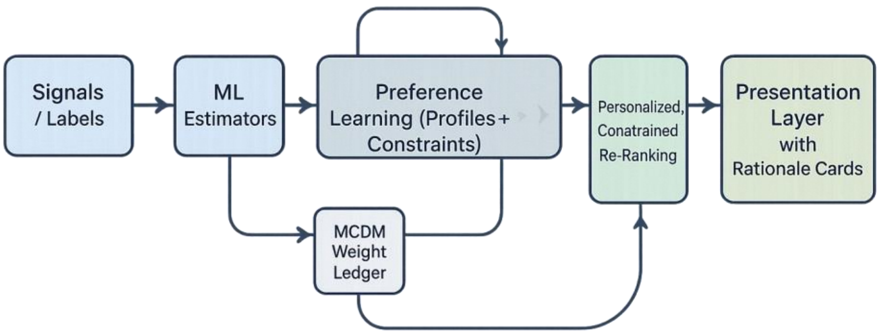

Figure 6. End-to-End Pipeline for Personalized Investment Decisions

In Table 7, the global ranking produced by the hybrid MCDM+ML framework is compared with personalized rankings for two investor personas, showing how the relative positions of Startups A–E are adjusted. For Persona A, who seeks a short horizon and low risk profile, Startup B is moved upward due to stable cashflows and low volatility, while Startup C is downgraded because of early-stage risk, and Startup D is ranked higher thanks to profitability and conservative debt. In this persona, Startup A is placed slightly lower because of runway concerns, while Startup E remains unchanged, reflecting the longer horizon required. For Persona B, with a long horizon and a climate-focused thesis, Startup A retains its top position due to strong IP and climate impact, while Startup C is ranked higher for its alliances and climate alignment. In contrast, Startup B is moved down because of limited climate relevance, Startup D falls further due to low climate contribution, and Startup E improves its ranking through Environmental, Social, and Governance (ESG) leadership and a robust partner network. These adjustments illustrate how general rankings of Startups A–E are reshaped when individual investment priorities are applied.

Table 7. General vs. Personalized rankings

Startup	Global Rank (MCDM+ML)	Persona A: Short-Horizon, Low Risk (Rank)	Why It Moved for A	Persona B: Long-Horizon, Climate Themed (Rank)	Why It Moved for B
A	1	2	Slightly lower runway; liquidity priority	1	Strong IP; climate impact
B	2	1	Stable cashflows; low volatility	3	Limited climate alignment
C	3	4	Early stage risk; A prefers maturity	2	Strong climate thesis; alliances
D	4	3	Profitable; conservative debt	5	Low climate relevance
E	5	5	Long horizon required	4	ESG leadership; partner network

Components and Governance of a Personalized Investment Decision Engine

A three-layer architecture has been proposed for finance-grade recommendation: an input layer that supplies a structured, auditable global list with criterion-level scores from MCDM+ML, a preference learning layer that infers investor profiles and policy constraints, and an output layer that performs constrained re-ranking and generates rationale-rich recommendations; finance-specific surveys have argued for domain-specific evaluation and data lineage in such designs (Wu & Li, 2025).

The data pipeline has been specified to include user interaction logs (views, comparisons, simulations), allocation decisions, post-allocation outcomes, and exogenous factor and sector exposures; it has been recommended that on-policy and off-policy evaluation be combined—offline counterfactual estimation to reduce production risk and online A/B testing to measure decision-time reduction, hit rate, and performance proxies—while shift detection triggers recalibration (Coussement et al., 2024). Documentation has been emphasized as part of audit readiness.

Explainability has been placed in two layers: global transparency from MCDM (criteria, weights, sensitivity) and local justification in recommendations (why an opportunity is suggested to this investor under current constraints); integration of XAI techniques with domain-meaningful artifacts has been associated with higher acceptance by decision makers (Kostopoulos et al., 2024). In practice, explanation cards have been used to present criterion contributions and constraint effects.

Risk and compliance have been enforced as hard or soft constraints within the re-ranking step; fairness diagnostics have been recommended to monitor exposure distributions across opportunity types and to prevent undesirable disparities; weight-change governance—with change control and human approval—has been proposed to maintain accountability for the MCDM layer (Jin et al., 2023; Jugovac et al., 2023). The integration of these processes has been advocated to ensure suitability and accountability.

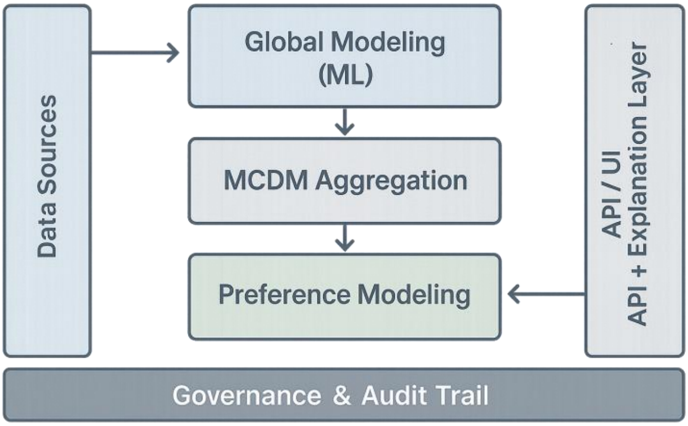

Figure 7. Architecture of a Personalized Investment Decision Engine

In Table 8, a structured governance checklist is presented, outlining key policies, enforcement points, evidence artifacts, frequencies, and responsible owners. Suitability requirements linked to investor profiles are enforced at the re-ranking layer, with evidence captured in suitability check logs for each recommendation under compliance oversight. Concentration and exposure caps are applied through re-ranking and portfolio policy, documented in constraint satisfaction reports on both batch and monthly basis, managed by risk teams. ESG exclusions are controlled prior to ranking, with exclusion list snapshots maintained for every update by ESG and risk functions. Fairness and exposure balance are monitored by re-ranking auditors, with distribution and disparity metrics reviewed weekly or monthly by data science and risk stakeholders. Weight change control in MCDM processes is governed through a bridge ledger, requiring change logs and formal approvals on each update, overseen by the investment committee and governance. Explainability is maintained globally through MCDM and locally within recommendation systems, supported by criteria plots and “why this” explanation cards on a continuous basis by product and data science teams. Drift and stability are tracked through ML monitoring, with drift alarms and recalibration notes continuously generated by data science and ML operations. Finally, audit trials are enforced across all layers, producing immutable decision logs under continuous compliance responsibility.

Table 8. Governance checklist

Policy / Risk Control	Where Enforced	Evidence Artifact	Frequency	Owner
Suitability (investor profile)	Re-ranking layer	Suitability check log	Per recommendation	Compliance
Concentration & Exposure Caps	Re-ranking + Portfolio policy	Constraint satisfaction report	Per batch & monthly	Risk
ESG Exclusions	Filter before ranking	Exclusion list snapshot	Per update	ESG/Risk
Fairness / Exposure Balance	Re-ranking auditor	Exposure distribution, disparity metrics	Weekly/monthly	Data Science + Risk
Weight Change Control (MCDM)	Weight ledger (bridge)	Change log + approvals	On change	IC / Governance
Explainability	Global (MCDM) + Local (Recommendation Systems)	Criteria/weight plots; “why this” cards	Continuous	Product/Data science (DS)

Policy / Risk Control	Where Enforced	Evidence Artifact	Frequency	Owner
Drift & Stability	ML monitoring	Drift alarms; recalibration notes	Continuous	DS/ML Operations
Audit Trail	All layers	Immutable decision log	Continuous	Complianc e

Conclusion and Future Directions

A coherent chain has been presented in which human–machine hybrid decision models are grounded in MCDM, coupled bidirectionally with ML, and extended into personalized decision engines for investment. The role of MCDM as a bridge has been emphasized because value judgments (weights) can be separated and governed while ML provides empirical estimates for criterion-level performance; the outcome is an auditable, adaptable, and explainable ranking for VC decisions (Martyn & Kadziński, 2023; Hüllermeier & Słowiński, 2024a, 2024b).

Future work has been suggested along four lines. First, dynamic weight learning and preference disaggregation should be advanced using revealed-preference data while preserving interpretability. Second, XAI tailored to investment should be developed, including counterfactual what-if analysis over criteria and constraints. Third, evaluation regimes that combine statistical metrics with decision-centric KPIs under regulatory constraints should be standardized for the domain. Fourth, fairness-aware re-ranking should be embedded to monitor exposure distributions across opportunity sets (Coussement et al., 2024; Jin et al., 2023). With these elements, hybrid MCDM–ML systems are expected to support personalized, trustworthy decision engines.

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CHAPTER 7

EVALUATION OF RENEWABLE ENERGY ALTERNATIVES IN COLD CLIMATE REGIONS: TOPSIS AND MOORA APPLICATION FOR ERZURUM TECHNICAL UNIVERSITY CAMPUS

ÖZLEM SÖKMEN[1]
DENİZ KATİPOĞLU[2]

Introduction

The rapid depletion of fossil fuel reserves and the increased use of these resources are causing greenhouse gas emissions, climate change and leading to global warming. Furthermore, the continuous increase in energy demand has made it imperative to use sustainable resources with lower environmental impacts. Indeed, the more widespread use of renewable energy sources has become a significant solution for both ensuring energy supply security and reducing carbon footprint. For Turkey, renewable energy sources hold significant importance due to their environmental, political, and economic benefits. Solar, wind, hydroelectric, geothermal, and

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biomass energy constitute the most widely used renewable energy sources in Turkey. Technical, economic, social, and geographical factors are taken into consideration while choosing renewable energy sources. Especially in cold climate regions, the selection of renewable energy sources is determined by analyzing specific technical and environmental factors. In this study, Erzurum Technical University (ETU) was selected as the sample region due to its location in one of Turkey's cold and high-altitude areas. Photovoltaic (PV), wind, and hybrid energy systems were analyzed in this study because of their high applicability at the campus scale and their suitability for grid-connected operations. The selection of PV, wind, and hybrid energy systems requires the simultaneous evaluation of numerous criteria, including economic, technical, and environmental factors. Based on this, in this study, various criteria were considered, and criterion weights were calculated using the Analytical Hierarchy Process (AHP) method, one of the multi-criteria decision-making (MCDM) methods. Furthermore, based on these calculated weights, the most suitable energy system alternative was determined using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) methods. The results obtained are expected to serve as a reference for settlements with similar climatic characteristics.

1. Renewable Energy Systems

Energy supply is provided through the use of fossil fuels and renewable energy sources. According to 2025 data, approximately 57-60% of Turkey's total installed electricity capacity is provided by renewable energy sources. Of these sources, wind accounts for 12% and solar for 20% (MENR, 2025). These figures show that wind and solar energy sources are increasingly becoming important in Turkey's energy policies.

Among renewable energy sources, solar and wind energy stand out for campus-scale energy production due to our country's favorable geographical location and the fact that they are easily installed systems that do not require high technology (Dikmen, 2019).

Photovoltaic (PV) energy systems are systems that convert incoming sunlight into usable energy. This provides a more environmentally friendly and secure energy option (Doğanay, 2021). Grid-connected PV systems, which operate connected to the central electricity grid and transfer excess energy back to the grid, are preferred on a campus scale (Güneş & Hacıoğlu, 2024). PV systems have both advantages and disadvantages in cold climates. Lower temperatures reduce heat loss in PV cells, increasing efficiency. However, icing, short days, and freezing conditions in winter limit energy production (Awad et al., 2018). When designing a PV system, considerations regarding the need for regular maintenance due to icing and snow events are necessary. Furthermore, PV energy systems offer a long-term, environmentally friendly, efficient, and economical energy source at a low cost (Aslam et al., 2022). However, they also have limitations due to their dependence on weather conditions, high storage costs, and the need for large areas for the panels. (Charfi et al., 2018). Many studies in the literature on PV energy systems show that Multi-Criteria Decision Making (MCDM) methods are widely used. In a study by Hassan et al. (2023), critical weights were determined for PV site selection using the CRITIC method, and the most suitable areas were determined by ranking alternatives using TOPSIS. In another study, PV panel type selection was determined by evaluating the TOPSIS method (Aslay, 2021). Çoban (2020) used fuzzy logic based on AHP to determine the critical weight for the selection of the most suitable PV-based project.

Wind energy systems are designed to convert the kinetic energy of the wind into electrical energy. Wind energy holds an important place among energy sources due to its continuity, cleanliness, and quality (Guo, 2025). With developing technology, small-scale wind turbines can be used if the selected region is suitable in terms of wind (Aslan et al., 2016). The effect of wind speed is very important in these energy systems; turbines are designed to operate optimally within specific speed ranges (Wang & Liu, 2021). Erzurum, being located in a high-altitude region, experiences more consistent and powerful wind speeds. This characteristic makes it an important location for the development of wind energy projects. However, icing, low air density, and extreme wind conditions negatively impact wind turbines. When designing wind turbines, various constraints such as efficiency, wind speed, turbine design, site location, and maintenance management must be considered (Ünal et al., 2024). MCDM methods have been widely used in the literature to determine the suitability of wind energy systems. In one study, a TOPSIS-based approach was proposed for determining the most suitable turbine for a selected site (Rehman, 2020). In a study conducted in 2024, the most suitable site for the installation of wind energy power plants in Adana province was determined through the integration of Analytical Hierarchy Process (AHP) and Geographic Information Systems (GIS) (Yaman, 2024). Supciller and Toprak (2020) calculated the critical weights for selecting the most suitable wind turbine for a large company operating in Turkey using the SWARA method. They then ranked the turbines using the TOPSIS and EDAS methods.

Hybrid energy systems are more efficient and environmentally friendly production systems that use a combination of different energy sources or technologies (Kılıç & Adalı, 2022). Hybrid systems that operate by using wind and solar energy together, both renewable energy sources, are widely used. Depending on the weather, photovoltaic solar panels and tiny wind turbines can generate different amounts of electricity. Therefore, they are not a very rich source of energy production on their own. By combining these sources into a single system, we can reduce fluctuations in energy production and gain many advantages (Çakmak, 2020). Thus, grid-connected hybrid systems provide a safer and more reliable energy source (Atik & Sekin, 2022). In cold climate regions, the decrease in sunshine duration during winter months and the increase in wind speeds demonstrate the advantages of hybrid systems. Furthermore, the installation of hybrid energy systems requires the analysis of numerous criteria such as system reliability, construction and operating costs, and maintenance requirements. Studies evaluating these criteria exist in the literature. In one study, the fuzzy TOPSIS method was used to evaluate renewable energy systems in Turkey. The results show that hybrid systems are suitable in terms of environmental criteria and energy supply security (Şengül, 2015). In another study, AHP-TOPSIS-COPRAS methods were applied comparatively for the site selection of a power plant in Kırıkkale (Kara et al., 2022). In the study by Ramos et al., the technical and economic suitability of hybrid renewable energy systems for a settlement in Portugal was evaluated using an MCDM approach (Ramos et al., 2025).

The literature shows that environmental, economic, technical, and social criteria should be evaluated simultaneously in the selection and planning of renewable energy systems. Appropriate evaluation of these characteristics has been carried out using MCDM methods. Simultaneous evaluation of these characteristics is also of great importance in renewable energy system projects in cold climate regions. Therefore, before proceeding with the selection of PV, wind, and hybrid energy systems for the campus area, the weighting of the criteria should be analyzed.

This study uses the AHP method to determine the importance levels of key criteria to consider before selecting grid-connected PV, wind, and hybrid energy systems. The suitability of each energy system alternative for the campus area was determined using the TOPSIS and MOORA methods, based on the importance levels of the criteria considered. The aim is to provide a roadmap for campuses in cold climate regions based on the results obtained.

2. Method

2.1. Analytic Hierarchy Process (AHP) Method

The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making (MCDM) methodology established by Thomas L. Saaty in the mid-1970s to address intricate decision-making challenges (Saaty & Niemira, 2006). The most important feature of AHP is its ability to integrate both subjective and objective thoughts and experiences of the decision-maker into the decision-making process within a logical framework (Özel & Türkel, 2018; Haliloğlu & Odabaş, 2021). The application steps of the AHP method are generally as follows (Saaty & Kearns, 1985; Saaty, 2005; Gökgöz et al., 2020):

Step 1: In this step, the decision problem is defined, and a hierarchical structure is established.

Step 2: The criteria defined in the model are evaluated through pairwise comparisons. For these comparisons, the 1-9 significance scale developed by Saaty and presented in Table 1 is used.

Step 3: After the pairwise comparison matrices are created, the matrix is normalized. This is done by dividing each cell value in the matrix by the column sum. Using Eq. (1), the normalized pairwise comparison matrix C is obtained.

$$bij = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{1}$$

Table 1 AHP Importance Weights

Importance Level	Definition
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2, 4, 6, 8	Intermediate values

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ . & . & \cdots & . \\ c_{n1} & c_{n2} & \cdots & c_{mn} \end{bmatrix} \tag{2}$$

By taking the row averages of the normalized matrix, the priority vector (W) showing the importance levels for each criterion is calculated as follows.

$$w_i = \frac{\sum_{j=1}^{n} c_{ij}}{n} \tag{3}$$

Step 4: The Consistency Ratio (CR) is calculated to check the consistency of the pairwise comparisons made by decision-makers. For the analysis to be consistent and acceptable, the calculated CR value must be less than 0.10. If the CR is not within this range, the decision-maker should reconsider their judgments. The CR is calculated using the Consistency Indicator (CI) and the Random Indicator (RI). After λ_{max} is calculated, CI is found using Eq. (4).

$$CI = \frac{\lambda \boldsymbol{max} - \mathrm{n}}{n-1} \tag{4}$$

Afterwards, the CR value is calculated by dividing the CI value by the RI value given in Table 2 using Eq. (5).

$$CR = \frac{CI}{RI} \tag{5}$$

Table 2 Consistency Index (CI)

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0,58	0,9	1,12	1,24	1,32	1,41	1,45	1,49

2.2. TOPSIS Method

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a MCDM method introduced by Hwang and Yoon in 1981 (Hwang & Yoon, 1981). The fundamental principle of this method is that the chosen alternative should be closest to the positive ideal solution and furthest from the negative ideal solution (Lai et al., 1994). In TOPSIS, the positive ideal solution (A^+) represents the best solution that maximizes the benefit criterion and minimizes the cost criterion, while the negative ideal solution (A^-) represents the worst solution (Tong et al., 2005). The method considers the alternative closest to the positive ideal solution as the best alternative, and Euclidean distances are used to program the distances (Wang & Elhag, 2006). The basic steps of the TOPSIS method are as follows (Triantaphyllou, 2000; Yurdakul & Iç, 2003; Mahmoodzadeh et al., 2007; Özden, 2011; Sevgin & Kundakcı, 2017; Genç et al., 2017):

Step 1: To achieve the decision-maker's goal, the problem, the criteria to be considered, and the alternatives to be ranked are determined.

Step 2: An initial decision matrix (A_{ij}) is created, with criteria in the columns and alternatives in the rows.

$$A_{ij} = \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & . & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & . & x_{2n} \\ . & . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . & x_{in} \\ . & . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & . & x_{mn} \end{bmatrix} \tag{6}$$

Step 3: The generated matrix is normalized so that all criteria can be compared in the same dimensionlessness. The elements of the normalized decision matrix are denoted by r_{ij} and calculated using Eq. (7).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \; (i = 1,2,\ldots.,m) \; (j = 1,2,\ldots.,n) \tag{7}$$

Step 4: The predefined criterion weights (w_j), which add up to 1, are multiplied by the normalized matrix values (r_{ij}) to obtain the weighted normalized decision matrix (V_{ij}).

$$\sum_{j=1}^{n} w_j = 1 \tag{8}$$

$$v_{ij} = w_j \; x \; r_{ij} \; (i = 1,2,\ldots.,m) \; (j = 1,2,\ldots.,n) \tag{9}$$

Step 5: Define the negative ideal and positive ideal solution values according to Eq. (10) and Eq. (11), respectively. Here, J represents the utility (maximization) criteria, J' represents the cost (minimization) criteria, X^- represents the least preferred negative ideal solution, and X^+ represents the most preferred positive ideal solution.

$$X^- = \{(\text{min}_i \text{v}_{ij} | \text{ j} \in \text{J}), (\text{maks}_i \text{v}_{ij} | \text{ j} \in J'), i = 1,2,\ldots.,m\} = \{V_1^-, V_2^-, \ldots, V_n^-,\} \tag{10}$$

$$X^+ = \{(\text{maks}_i \text{v}_{ij} | \text{ j} \in \text{J}), (\text{min}_i \text{v}_{ij} \big| \text{ j} \in J'\big), i = 1,2,\ldots.,m\} = \{V_1^+, V_2^+, \ldots, V_n^+,\} \tag{11}$$

Step 6: The Euclidean distances of each alternative from the negative and positive ideal solutions are calculated using Eq. (12) and Eq. (13).

$$S_i^{+}= \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{+})^2} \quad (i = 1,2,\ldots.,m) \qquad (12)$$

$$S_i^{-}= \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{-})^2} \quad (i = 1,2,\ldots.,m) \qquad (13)$$

Step 7: In this step, the relative proximity of each alternative to the ideal solution is calculated using Eq. (14). This value is between 0 and 1, and the alternative with the largest value is considered the best alternative.

$$C_i^{*} = \frac{S_i^{-}}{S_i^{-}+S_i^{+}} \; (i = 1,2,\ldots.,m) \qquad (14)$$

2.3. MOORA Method

MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) is a multi-objective decision-making method based on ratio analysis, originally introduced by Brauers and Zavadskas in 2006. The method holistically addresses the interactions between selection criteria and objectives (Brauers & Zavadskas, 2006). The stages of the MOORA method are as follows (Brauers et al., 2008; Metin et al., 2017; Orhan et al., 2023):

Step 1: First, an initial decision matrix is created. Here, "*m*" represents the number of alternatives; "*n*" represents the total number of criteria; and x_{ij} represents the value of the *i.* alternative in the *j.* objective.

$$X = \begin{bmatrix} x_{11} & x_{1i} & x_{1n} \\ . & . & . \\ . & . & . \\ x_{j1} & x_{ji} & x_{jn} \\ . & . & . \\ . & . & . \\ x_{m1} & x_{mi} & x_{mn} \end{bmatrix} \tag{15}$$

Step 2: The decision matrix values are normalized using Eq. (16).

$$x'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \tag{16}$$

Step 3: In this stage, the criteria in the normalized decision matrix are classified as benefit (maximization) and cost (minimization) criteria according to the level of contribution they provide to the business. The values of the criteria that need to be maximized are summed up, while the sum of the criteria that need to be minimized is subtracted from this value. The MOORA score is calculated using Eq. (17), where $j = 1,2,\ldots,g$ represents the benefit criteria and $j = g + 1, g + 2,\ldots,n$ represents the cost criteria.

$$y_i^* = \sum_{i=1}^{i=g} x'_{ij} - \sum_{i=g+1}^{i=n} x'_{ij} \tag{17}$$

After completing these steps, the resulting y_i^* values are sorted from largest to smallest. The alternative with the highest value in this sorting process is then considered the most suitable option for the decision problem.

3. Application

In this section, the defined multi-criteria decision-making model was applied to the Erzurum Technical University campus, located in one of Turkey's high-altitude regions with harsh winter conditions. The application phase of the study involved measuring the performance of grid-connected PV, wind, and hybrid energy systems, determined based on the region's climatic data and the campus's energy needs. In the first stage, the importance weights of the criteria were determined using pairwise comparison matrices created based on expert opinions and the AHP method. Based on these weights, the proximity of the alternatives to the ideal solution was analyzed using the TOPSIS method, and the benefit-cost balance was analyzed using the MOORA method. The analysis process was completed by comparing the results of these methods with different algorithms and identifying the most sustainable energy model for the campus.

3.1. Definition of the Criteria Set

The criteria for this study were determined by considering a literature review, applications in renewable energy systems, and the opinions of expert academics and industry representatives. Furthermore, the technical characteristics of grid-connected PV, wind, and hybrid energy systems were examined. Energy infrastructures in cold climate regions, particularly in university campuses, were investigated, and a final evaluation framework with 10 criteria was created. These criteria encompass technical, economic, environmental, and social factors affecting the applicability of PV, wind, and hybrid energy systems. Brief descriptions of each criterion are shown in Table 3.

The 10 key criteria used in the analysis process were divided into two groups, benefit and cost, according to their impact on the decision-making model. Accordingly, Regional Energy Potential (C1), Resilience and Efficiency under Climatic Conditions (C2), System Reliability and Continuity (C3), Grid Connection and Integration Suitability (C4), Land Conditions and Topography (C8), Regional and National Incentive Opportunities (C9), and Environmental Impact and Emission Reduction (C10) criteria were defined as benefit criteria where high values were preferred. In contrast, Initial Investment Cost (C5), Payback Period (C6), and Operating and Maintenance Costs (C7), representing the economic burden of the system, were included in the model as cost criteria where low values were targeted.

Table 3 Criteria and Definitions

No	Criterion Name	Criterion Description
C1	Regional Energy Potential	Solar irradiation duration, wind speeds, seasonal variations
C2	Resilience and Efficiency under Climatic Conditions	Snow load, low-temperature performance, icing effects
C3	System Reliability and Continuity	Failure rate, operational continuity
C4	Grid Connection and Integration Suitability	Infrastructure compatibility, connection cost, technical requirements
C5	Initial Investment Cost	Capital expenditures
C6	Payback Period (PP)	Financial return
C7	Operating and Maintenance Costs	Maintenance frequency and component durability in cold climates
C8	Land Conditions and Topography	Installation orientation, impact of slope on efficiencyand slope effect on efficiency
C9	Regional and National Incentive Opportunities	Government incentives, tax benefits
C10	Environmental Impact and Emission Reduction	CO_2 reduction contribution, impact on the campus environment

The 10 key criteria used in the analysis process were divided into two groups, benefit and cost, according to their impact on the decision-making model. Accordingly, Regional Energy Potential (C1), Resilience and Efficiency under Climatic Conditions (C2), System Reliability and Continuity (C3), Grid Connection and Integration Suitability (C4), Land Conditions and Topography (C8), Regional and National Incentive Opportunities (C9), and Environmental Impact and Emission Reduction (C10) criteria were defined as benefit criteria where high values were preferred. In contrast, Initial Investment Cost (C5), Payback Period (C6), and Operating and Maintenance Costs (C7), representing the economic burden of the system, were included in the model as cost criteria where low values were targeted.

After the criteria were determined as shown in Table 3, evaluation forms were prepared. Interviews were conducted with academics and experts experienced in renewable energy systems and regional applications to ensure the reliability of the decision-making process. To determine the importance levels of these criteria and to create pairwise comparison matrices, the opinions of three Electrical-Electronics Engineers specializing in energy systems were consulted. Literature research has shown that multiple MCDM methods are used together to solve similar decision-making problems. It has been emphasized that this strengthens the consistency of the results obtained. Accordingly, in this study, different MCDM methods were used for analysis, and the criterion weights confirmed the validity of the decision results.

3.2. Calculation of Criteria Weights Using the AHP Method

Within the scope of the study, the individual evaluations of three expert engineers were combined using the geometric mean method in accordance with the group decision-making process. This ensured the reduction of subjectivity and the gathering of expert opinions on a common denominator. A pairwise comparison matrix of size 10x10 was created using the 1-9 scale given in Table 1. The steps of the AHP method were followed and the normalized decision matrix was obtained using Eq. (1). The normalized decision matrix created is presented in Table 4. In the next stage, the criterion weights obtained using Eq. (3) are presented in Table 5 in order of importance.

Table 4 Normalized Decision Matrix

Crit.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0.249	0.437	0.308	0.363	0.262	0.254	0.120	0.194	0.131	0.081
C2	0.059	0.104	0.125	0.147	0.163	0.158	0.120	0.113	0.081	0.081
C3	0.101	0.104	0.125	0.147	0.163	0.133	0.120	0.101	0.096	0.075
C4	0.070	0.072	0.087	0.102	0.198	0.192	0.134	0.093	0.081	0.139
C5	0.063	0.042	0.051	0.034	0.066	0.092	0.173	0.076	0.156	0.165
C6	0.090	0.061	0.087	0.049	0.066	0.092	0.194	0.210	0.251	0.185
C7	0.146	0.061	0.073	0.053	0.027	0.033	0.070	0.134	0.121	0.081
C8	0.040	0.028	0.038	0.034	0.027	0.014	0.016	0.031	0.033	0.071
C9	0.063	0.042	0.043	0.041	0.014	0.012	0.019	0.031	0.033	0.081
C10	0.120	0.050	0.065	0.029	0.016	0.020	0.034	0.017	0.016	0.039

Table 5 Criteria Weight Values

Rank	Code	Criterion Name	Weight (w_j)
1	C1	Regional Energy Potential	0,241
2	C6	Payback Period (PP)	0,128
3	C4	Grid Connection and Integration Suitability	0,117
4	C3	System Reliability and Continuity	0,116
5	C2	Resilience and Efficiency under Climatic Conditions	0,115
6	C5	Initial Investment Cost	0,092
7	C7	Operating and Maintenance Costs	0,080
8	C10	Environmental Impact and Emission Reduction	0,040
9	C9	Regional and National Incentive Opportunities	0,038
10	C8	Land Conditions and Topography	0,033

As seen in Table 5, the criterion with the highest importance in the study was “Regional Energy Potential” with a weight of 0.241, while the criterion with the lowest weight was “Land Conditions and Topography” with a weight of 0.033. Furthermore, the consistency ratio obtained from the AHP consistency analysis (CR < 0.10) was found to be within acceptable limits, and the comparison matrix was determined to be consistent.

3.3. Evaluation and Ranking of Alternatives

In this phase of the study, the performance of the alternatives (PV, wind, and hybrid energy systems) determined using the criterion weights (w_j) obtained by the AHP method was evaluated. To confirm the accuracy of the results and observe the effect of different mathematical algorithms on the ranking, the TOPSIS and MOORA methods were used together in the analysis process. These methods normalize the criterion-based performance of the alternatives, transforming them into a comparable structure and generating a final success score for each alternative.

3.3.1. Evaluation Using the TOPSIS Method

After normalization and weighted matrix vector normalization, each value was multiplied by the relevant criterion weight w_j as shown in Eq. (9) to create the weighted normalized decision matrix, which is presented in Table 6.

Table 6 Weighted Normalized Decision Matrix

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
PV Energy (A1)	0.147	0.067	0.062	0.058	0.066	0.079	0.051	0.013	0.019	0.021
Wind Energy (A2)	0.121	0.055	0.055	0.065	0.043	0.065	0.034	0.024	0.024	0.026
Hybrid Energy (A3)	0.147	0.075	0.082	0.077	0.048	0.079	0.051	0.019	0.022	0.023

The best (ideal) and worst (negative ideal (NI)) performance values for each criterion are determined below and given in Table 7.

Table 7 Ideal (X^+) and Negative Ideal (X^-) Solution Values

Values	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Ideal (X^+)	0.147	0.075	0.082	0.077	0.043	0.065	0.034	0.024	0.024	0.026
NI (X^-)	0.121	0.055	0.055	0.058	0.066	0.079	0.051	0.013	0.019	0.021

In the next step, the distances of each alternative to the ideal solutions, S_i^+ and S_i^-, using Eq. (12) and Eq. (13), and the relative proximity coefficients (C_i^*) obtained using Eq. (14) are presented in Table 8.

Table 8 Distances of Alternatives from Positive and Negative Ideal Solutions

Alternative	S_i^+	S_i^-	C_i^*	Rank
A3	0.023	0.050	0.686	1
A2	0.044	0.035	0.444	2
A1	0.045	0.029	0.398	3

Examining the C_i^* coefficients given in Table 8, it is seen that alternative A3 (hybrid energy system) is the best option with a score of 0.686. According to the TOPSIS logic, this result shows that A3 is the alternative closest to the determined ideal criterion values and furthest from the negative ideal values. The significant score difference between A2 (wind energy system), which is in second place, and A3, which is in first place, stems from A3's dominant performance, especially in the high-weighted criteria (C1, C3, C4). Alternative A1 (PV energy system) ranked last in the evaluation with a score of 0.398.

3.3.2. Evaluation Using the MOORA Method

Normalization and weighting of the standard decision matrix for the MOORA method is the same as in the TOPSIS method. In the next step, using Eq. (17), the sum of the cost criteria is subtracted from the sum of the benefit criteria to obtain the net values (y_i^*). In this context, the values of the benefit-oriented criteria (C1, C2, C3, C4, C8, C9, C10) and the cost-oriented criteria (C5, C6, C7) are summed separately. The benefit/cost totals are given in Table 9.

Table 9 Benefit/Cost Totals

Alternative	Total Benefit	Total Cost
PV Energy System (A1)	0.388	0.195
Wind Energy System (A2)	0.370	0.141
Hybrid Energy System (A3)	0.445	0.177

In the final stage, net performance values were obtained by subtracting total costs from total benefits, and these are given in Table 10.

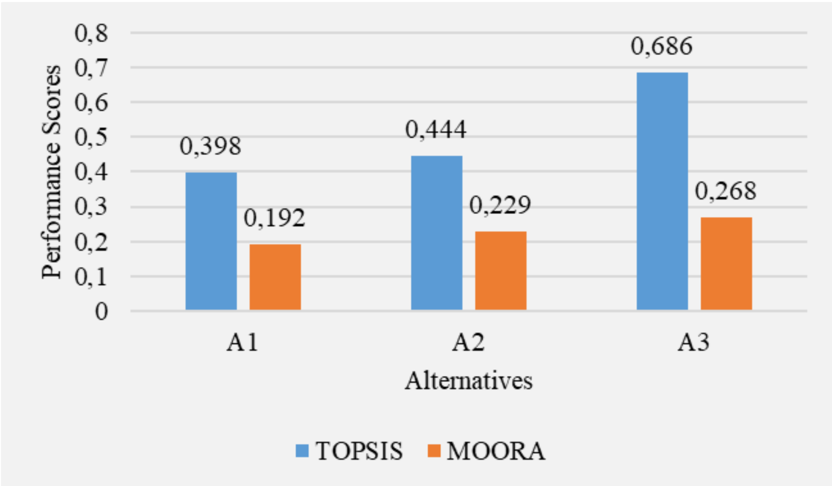
Table 10 MOORA Score Values

Alternative	y_i^*	Rank
A3	0,268	1
A2	0,229	2
A1	0.192	3

The y_i^* scores obtained from the MOORA analysis support the TOPSIS results. Alternative A3 (hybrid energy system) ranked first with a net score of 0.268, confirming it to be the most suitable option. The MOORA method, by clearly subtracting the effect of cost criteria (C5, C6, C7) from the total, confirms that A3 has both a high benefit and an acceptable cost balance. The results obtained with both methods are summarized comparatively in Figure 1.

As shown in Figure 1, both analysis methods confirmed the consistency of the results by ranking alternative A3 (hybrid energy) in first place with the highest score. The significant difference in TOPSIS scores, in particular, is a numerical indicator of A3's closeness to the ideal solution.

Figure 1 Comparative Performance Scores of Alternatives According to Methods



4. Conclusion and Recommendations

This study presents an integrated decision-making model to determine the most suitable grid-connected renewable energy system for the ETU campus. In the study area, which represents Turkey's cold climate and high altitude characteristics, PV, wind, and hybrid systems (A1, A2, A3) were evaluated under 10 different technical, economic, and environmental criteria. The weighting process, carried out using the AHP method, revealed that the most decisive factor in energy investments in cold climate regions is "C1: Regional Energy Potential" with a weight of 24.1%. This finding confirms the need for specific analysis of high-altitude regions. The fact that the second most important criterion is "C6: Payback Period (PP) (12.8%)" demonstrates the priority of economic sustainability for campus-scale investments.

Both TOPSIS and MOORA analyses ranked the hybrid energy system (A3) first with the highest performance score. In the TOPSIS method, alternative A3 was determined to be the closest option to the ideal solution with a success coefficient of 0.686. In the MOORA method, the net score of 0.268 confirmed that the benefit-cost balance of system A3 is superior to other alternatives (PV and wind). The fact that both different MCDM methods produced the same ranking (A3 > A2 > A1) shows that hybrid systems (combination of solar and wind) are the most stable solution for regions with challenging climatic conditions like Erzurum.

According to the results of the study, it can be said that priority should be given to the installation of hybrid systems in which grid-connected PV and wind turbines work together to ensure energy supply security and minimize the carbon footprint on the ETU campus. This structure will maximize the continuity of the system (C3 criterion) by utilizing wind energy during hours when solar radiation is low. In the design of the systems to be installed, panel and turbine technologies that offer high efficiency at low temperatures should be preferred, taking into account the high weight of the "C2: Resilience and Efficiency under Climatic Conditions" criterion. It is predicted that the weight of the "C9: Regional and National Incentive Opportunities" criterion, which has a low weight in the analysis, may increase with future local government and ministry support; this situation is considered to further shorten the return on investment period (C6).

The criterion weights and ranking results obtained in this study can be used as a strategic planning guide for other settlements and public campuses with similar climate and topographical characteristics. Several suggestions are presented for future studies to expand the scope of the findings and make the decision-making process more dynamic. To minimize uncertainties in decision-makers' evaluations, the model's sensitivity can be increased by using fuzzy logic versions of AHP, TOPSIS, and MOORA methods. The stability of the results can be tested by including MCDM techniques with different algorithms such as VIKOR, PROMETHEE, or ELECTRE in the current model. Furthermore, comprehensive sensitivity analyses can be performed to measure the impact of possible changes in criterion weights and economic data (incentives, costs, etc.) on the ranking.

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CHAPTER 8

PICTURE FUZZY-BASED ASSESSMENT OF SUSTAINABLE DEVELOPMENT PERFORMANCE OF EUROPEAN COUNTRIES BORDERING THE MEDITERRANEAN

HALİL ŞEN[1]

Introduction

Sustainable development is a multidimensional development approach that aims to achieve economic growth, social inclusion, and environmental protection goals together and in a balanced manner. This approach has been transformed into a globally measurable policy framework with the 17 Sustainable Development Goals (SDGs) defined within the 2030 Agenda adopted by the United Nations in 2015; a comprehensive monitoring architecture has been established for monitoring and comparing the performance of countries. However, measuring SDG performance is not only a problem of bringing together numerous indicators, but also a decision analytics problem where methodological choices such as indicator selection, normalization, weighting, and composite indexing can significantly alter country rankings. Indeed, the

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literature clearly emphasizes that SDG rankings are highly sensitive to the indicators used and methodological assumptions; different methodological approaches can significantly change the relative positions of countries (Lafortune et al., 2020; Miola & Schiltz, 2019). Similarly, the need for "appropriate indicators" is critical in measuring SDG goals; The need to establish a consistent framework for indicators in terms of their meaningfulness and representativeness is also a key area of discussion (Hák et al., 2016).

European countries bordering the Mediterranean share common areas of vulnerability such as climate change, water stress, energy transition, tourism pressure, urbanization, and socioeconomic inequalities. Therefore, a comparative analysis of the SDG performance of this group of countries is important both for regional sustainability policies and for making the priority sets of countries visible. However, the heterogeneity of data, incomplete observations, structural differences between countries, and uncertainty in interpreting trend indicators such as "progress/regression" can limit the explanatory power of classical exact comparison methods in the evaluation of SDG indicators. In addition, since SDG evaluations are often carried out with composite indices based on a high degree of compensatory power, it is possible for success in one dimension to mask weakness in another dimension; This situation can lead to misleading results in policy inferences (Hametner & Kostetckaia, 2020; Miola & Schiltz, 2019).

In this study, a Picture Fuzzy Set (PFS) based integrated multi-criteria decision-making (MCDM) approach is proposed to reduce these methodological difficulties and to enable the evaluation of SDG performance with a more flexible uncertainty representation. Unlike classical fuzzy sets, the PFS approach represents the uncertainty in decision-maker judgments more realistically by modeling not only the degree of "membership" but also the degrees of "undecided/abstaining" and "opposition" together (Cường, 2014).

Since the selection of appropriate aggregation operators is critical for combining multi-criteria information in PFS-based decision problems, the Picture Fuzzy Interactional Bonferroni Mean (PF-IBM) operator, which stands out for its ability to capture inter-criteria interactions, is used in this study. Bonferroni average is a powerful tool in multi-criteria aggregation because it can account for the interrelationships between criteria through a partial multiplier structure (Beliakov et al., 2010; Yager, 2009). The development of PF-IBM operators in the PFS environment and the demonstration of their applicability to MCDM have been particularly emphasized in recent literature (Ateş & Akay, 2020; Liu et al., 2023). In this context, the study aims to transform the SDG performance of European countries bordering the Mediterranean Sea within the PFS framework, generate SDG-based scores using PF-IBM, and rank the countries. On the other hand, to test the reliability of the rankings obtained with the method and to evaluate the consistency of the results under an alternative consensus-based method, the Picture Fuzzy CoCoSo (PF-CoCoSo) approach is used within the scope of robustness analysis. The CoCoSo method combines additive weighting and exponential weighting logic to produce a "consensus"-based solution and is a powerful ranking tool widely used in the MCDM literature (Yazdani et al., 2019). CoCoSo is also used in the context of SDG; for example, it has been shown that the integration of CoCoSo and Shannon entropy produces objective results in the assessment of SDG progress in EU countries (Stanujkic et al., 2020). Furthermore, it has been shown that normalization preferences have a strong impact on the results in the CoCoSo algorithm, and appropriate normalization is a critical design decision (Ersoy, 2022). In this study, testing the findings obtained with PF-IBM under PF-CoCoSo provides a validation layer that strengthens the methodological stability of the results. Thus, this study aims to contribute to literature by proposing a holistic framework that (i) models the uncertainty of SDG performance with PFS, (ii) accounts for criterion interactions with PF-IBM, and (iii) tests ranking robustness with PF-CoCoSo.

The measurement and cross-country comparison of SDG performance is rapidly expanding as both methodological and policy-oriented research area in the literature. While indices created with SDG indicators are functional in increasing country accountability and making progress towards the 2030 goals visible, the high sensitivity of rankings to methodological preferences stands out as a significant problem. Miola & Schiltz (2019), in their study on the EU-28 sample, compared the three most common SDG ranking approaches and showed that country positions can change almost entirely depending on the chosen indicator set and assumptions. Similarly, Lafortune et al. (2020), emphasized that there is no “single correct approach” to measuring SDG progress in the EU context; factors such as the definition of targets/trajectories, cross-border impacts, and how data gaps are closed determine the results. These findings have highlighted the limitations of classical single-method indices in SDG performance assessment, paving the way for alternative frameworks based on MCDM.

The use of MCDM methods in SDG assessments has become widespread, both in terms of weighting indicators and aggregating multidimensional performance. For example, Mateusz et al. (2018), examined the sustainable development indicators of EU countries using TOPSIS and VIKOR, discussing method sensitivity and the impact of method selection on the results. Rocchi et al. (2022), proposed a multi-criteria-based SDG achievement index (SDG-AI) to measure SDG performance; they discussed inter-dimensional consistency and the impact of the pandemic. Ricciolini et al. (2022), on the other hand, examined the progress of SDG implementation in European countries using multi-criteria methods with partial compensatory based on multiple reference points, revealing clusters of countries that experienced difficulties, particularly in social and economic dimensions. In addition, studies highlighting the importance of the time dimension and absolute progress measure in SDG monitoring show that relative rankings can misleadingly produce “leader/lagging” labels (Hametner & Kostetckaia, 2020). These discussions indicate that SDG performance should be considered not only in a single cross-section, but also taking into account the nature of the indicators and the dynamics of progress.

One of the fundamental problems of SDG measurement is the appropriateness and representativeness of the indicators. Hák et al. (2016), argued that in the operationalization of SDG targets, the “indicator-represented phenomenon” relationship of the indicators must be clearly established, otherwise the measurements will produce ambiguous messages. This problem, especially when combined with inter-country heterogeneity and differences in data quality, justifies the use of fuzzy approaches that explicitly represent uncertainty. At this point, the Picture Fuzzy Set (PFS) approach offers a strong theoretical framework because it can directly model the components of uncertainty and instability in evaluations. Cường (2014), defined the PFS concept and proposed an uncertainty representation using degrees of undecidedness/abstention and opposition in addition to membership degree; he showed that PFS provides higher expressive power than intuitive fuzzy sets. The use of PFS in conjunction with aggregation operators in the context of MCDM has been increasing in the literature. Garg (2017), presented a viable decision procedure for multi-criteria decision making by developing various aggregation operators (weighted average, ordinal weighted average, and hybrid average) under PFS. One of the critical steps in PFS-based decision problems is selecting the appropriate aggregation operator that captures the relationships between criteria. In this context, the Bonferroni mean family has gained an important place in multi-criteria aggregation because it partially accounts for inter-criteria interactions through a multiplier structure. Yager

(2009), emphasized the capacity of the Bonferroni mean operator to capture inter-criteria relationships by interpreting it within multi-criteria aggregation functions; Beliakov et al. (2010), systematically examined generalized forms of Bonferroni mean operators, revealing a broad family capable of modeling partial combination/decomposition and tolerance concepts. This theoretical foundation paved the way for the development of interactive Bonferroni types in a fuzzy environment. In the PFS environment, Bonferroni-based operators have been particularly concretized with the Picture Fuzzy Interactional Bonferroni Mean (PF-IBM) approach. Ateş & Akay (2020), proposed a multi-criteria decision-making procedure by developing Bonferroni mean and its derivatives (including normalized weighted and ordinal weighted forms) under PFS and demonstrated the applicability of the method through application. Liu et al. (2023), developed PF-IBM and related operators (PFIWBM, PFINWBM) based on strict triangular norms, proved their basic properties, and also proposed a new MCDM method in the PFS environment, reporting that it yielded consistent selections under different triangular norm classes when used in the ERP selection problem. These studies show that PF-IBM is a powerful aggregation and ranking tool, especially in problems with high uncertainty and criterion interaction. Therefore, the use of PF-IBM in performance evaluations consisting of multidimensional and interconnected objectives such as SDG is theoretically supported.

In recent years, the integration of robustness/sensitivity analyses into MCDM studies has become widespread in order to increase the reliability of the obtained rankings. In this context, the CoCoSo (Combined Compromise Solution) method is noteworthy because it produces a consensus-based score by combining different aggregation logics (aggregate weighting and exponential multiplication structure). Yazdani et al. (2019), proposed the CoCoSo method for MCDM problems; By discussing the comparative performance and sensitivity analyses of the method on a real logistics/transportation selection problem, the method's unique contribution has been demonstrated. As an example of CoCoSo's applications in the context of sustainability and SDGs, Stanujkic et al. (2020), obtained an objective ranking by evaluating the progress of EU countries towards SDG achievement using CoCoSo and Shannon entropy, and discussed the structural differences between the countries in the upper and lower groups. Ersoy (2022), showed through a scenario-based comparison that the normalization step is critical in the algorithmic design of CoCoSo, and that different normalization procedures can change the results. Fuzzy extensions of CoCoSo are also expanding in the literature; for example, Karasan & Bolturk (2019), demonstrated the applicability of the method to uncertain and indeterminate decision problems by adapting it to an interval-valued neutrosophic environment; while Kumar & Kumar (2024), performed sustainable biomass crop selection with an extended CoCoSo framework in an intuitive fuzzy environment and examined the stability of the results with sensitivity analysis. These developments demonstrate that CoCoSo is a family of methods suitable for use in different uncertainty environments for the purpose of “robustness” and “validation”. The placement of this study in the literature is that it establishes a master-ranking approach that addresses the problems of method sensitivity and indicator selection in SDG performance measurement (Miola & Schiltz, 2019; Lafortune et al., 2020; Hák et al., 2016), models uncertainty with PFS (Cường, 2014; Garg, 2017), and captures criterion interactions with Bonferroni/IBM-based interactive operators (Yager, 2009; Beliakov et al., 2010; Ateş & Akay, 2020; Liu et al., 2023). In addition, the consistency and methodological stability of the obtained results are tested with PF-CoCoSo, thus applying the consensus-based validation logic from the CoCoSo literature to the SDG problem (Yazdani et al., 2019; Stanujkic et al., 2020; Ersoy, 2022). Therefore, this study aims to evaluate the SDG performance in European countries bordering the Mediterranean Sea using an integrated picture fuzzy MCDM framework that can represent uncertainty while also incorporating interaction and robustness elements.

Method

This study proposes an integrated Picture Fuzzy (PF) multi-criteria decision-making (MCDM) framework to evaluate the sustainable development performance of European countries bordering the Mediterranean Sea based on Sustainable Development Goal (SDG) indicators. The research design consists of four main stages: (i) construction of the dataset and definition of the decision problem, (ii) transformation of SDG indicators into picture fuzzy numbers, (iii) computation of SDG-based performance scores and country rankings using the Picture Fuzzy Interactional Bonferroni Mean (PF-IBM) method, and (iv) robustness analysis of the obtained results using the Picture Fuzzy CoCoSo (PF-CoCoSo) method. Since SDG performance assessments are highly sensitive to indicator selection and methodological choices, as emphasized in the literature, the main ranking is derived using PF-IBM, while the consistency and reliability of the results are examined through an alternative compromise-based approach.

The set of alternatives is defined as;

$$A = \{A_1, A_2, \dots, A_m\},$$

representing the European countries bordering the Mediterranean. The criteria set;

$$C = \{C_1, C_2, \dots, C_n\}$$

corresponds to the selected SDG dimensions. For each country–SDG pair, two complementary types of information are used: the SDG Dashboard (Rating), which reflects the current level of performance, and the SDG Trend, which captures the direction and pace of progress. By jointly considering both dimensions, the analysis incorporates not only the present status of sustainability but also its dynamic evolution.

To adequately model uncertainty, incompleteness, and interpretative ambiguity in SDG assessments, each country–SDG evaluation is represented using Picture Fuzzy Numbers (PFNs). A PFN is defined as;

$$\tilde{x}_{ij} = \left(\mu_{ij}, \eta_{ij}, \nu_{ij}\right), 0 \leq \mu_{ij} + \eta_{ij} + \nu_{ij} \leq 1,$$

where μ_{ij}, η_{ij}, and ν_{ij}denote the degrees of membership (success), neutrality (hesitation), and non-membership (failure), respectively. In this study, SDG Dashboard and SDG Trend indicators are converted into PFNs using a predefined linguistic-to-numerical transformation scale. The underlying logic of this transformation is that high SDG performance is associated with a high membership degree, low performance with a high non-membership degree, and intermediate or ambiguous conditions with a higher neutrality degree. Accordingly, two PFNs are defined for each country–SDG pair:

$$\tilde{r}_{ij} = (\mu_{ij}^{r}, \eta_{ij}^{r}, \nu_{ij}^{r})\text{(Dashboard PFN)},$$
$$\tilde{t}_{ij} = (\mu_{ij}^{t}, \eta_{ij}^{t}, \nu_{ij}^{t})\text{(Trend PFN)}.$$

To integrate the current performance level and the progress trend into a single assessment, these two PFNs are aggregated using a weighted linear combination:

$$\tilde{x}_{ij} = \alpha\tilde{r}_{ij} + (1-\alpha)\tilde{t}_{ij}, 0 \leq \alpha \leq 1.$$

Component-wise, this aggregation is computed as

$$\mu_{ij} = \alpha\mu_{ij}^{r} + (1-\alpha)\mu_{ij}^{t},$$
$$\eta_{ij} = \alpha\eta_{ij}^{r} + (1-\alpha)\eta_{ij}^{t},$$
$$\nu_{ij} = \alpha\nu_{ij}^{r} + (1-\alpha)\nu_{ij}^{t}.$$

When necessary, normalization is applied to ensure that the condition $\mu_{ij} + \eta_{ij} + \nu_{ij} \leq 1$is satisfied. As a result, the picture fuzzy decision matrix

$$\tilde{X} = [\tilde{x}_{ij}]_{m\times n}$$

is obtained.

The criteria weights are defined as;

$$w = (w_1, w_2, \dots, w_n),$$

subject to the constraints;

$$w_j \geq 0, \sum_{j=1}^{n} w_j = 1.$$

Weights are determined either by equal weighting, to preserve methodological neutrality, or by objective data-driven approaches, depending on the analytical scenario. The same weight vector is consistently used across PF-IBM and PF-CoCoSo analyses to ensure comparability.

To compute the overall SDG performance of each country, the Picture Fuzzy Interactional Bonferroni Mean (PF-IBM) operator is employed. Unlike traditional aggregation operators, PF-IBM explicitly accounts for interactions among criteria by evaluating the contribution of each criterion together with the average influence of the others. The general form of the PF-IBM operator is expressed as

$$\text{PF-IBM}(\tilde{x}_1, \dots, \tilde{x}_n) = \frac{1}{n(n-1)} \sum_{i\neq j} \tilde{x}_i \otimes \tilde{x}_j,$$

where $\otimes$denotes the picture fuzzy multiplication operation. The weighted PF-IBM operator for country $A_i$is given by

$$\tilde{S}_i = \text{PF-IBM}(\tilde{x}_{i1}, \tilde{x}_{i2}, \dots, \tilde{x}_{in}; w) = \left(\sum_{j\neq k} w_j\, w_k (\tilde{x}_{ij} \otimes \tilde{x}_{ik}) \right)^{1/2}$$

This aggregation yields a single picture fuzzy performance value

$$\tilde{S}_i = (\mu_i, \eta_i, \nu_i)$$

for each country.

To obtain a crisp ranking, PFNs are transformed into scalar values using a score function defined as

$$\text{Score}(\tilde{S}_i) = \mu_i - \nu_i - \lambda\eta_i, \lambda > 0,$$

where $\lambda$is a balancing parameter controlling the influence of the neutrality degree. Countries are ranked in descending order of their score values, resulting in the PF-IBM-based SDG performance ranking.

In the final stage, the robustness of the obtained ranking is examined using the Picture Fuzzy CoCoSo (PF-CoCoSo) method. PF-CoCoSo is a compromise-based MCDM approach that integrates additive and multiplicative utility principles within a picture fuzzy environment. Based on the picture fuzzy decision matrix, two utility measures are computed for each country: the additive utility

$$S_i = \sum_{j=1}^{n} w_j \cdot \text{Score}(\tilde{x}'_{ij}),$$

and the multiplicative utility

$$P_i = \prod_{j=1}^{n} [\text{Score}(\tilde{x}'_{ij})]^{w_j},$$

where $\tilde{x}'_{ij}$denotes the normalized picture fuzzy evaluations. These two measures are then combined into a compromise score:

$$K_i = \lambda_c \left(\frac{S_i}{\max_i S_i} \right) + (1 - \lambda_c) \left(\frac{P_i}{\max_i P_i} \right), 0 \leq \lambda_c \leq 1.$$

The parameter $\lambda_c$controls the relative importance of additive and multiplicative components and is typically set to 0.5 to ensure balance. Countries are ranked according to their $K_i$values, and the resulting PF-CoCoSo ranking is compared with the PF-IBM ranking using rank correlation coefficients, top-k overlap analysis, and sensitivity analysis with respect to λ_c. This procedure allows the stability and methodological robustness of the proposed PF-IBM-based SDG performance assessment to be rigorously evaluated.

As shown below, the algorithm of the PF-IBM–PF-CoCoSo Framework for Sustainable Development Goals Performance Assessment is as follows:

- Step 1: Data preparation Collect SDG Dashboard and SDG Trend indicators for each country–SDG pair (A_i, C_j).
- Step 2. Transformation to Picture Fuzzy Numbers (PFNs) Convert Dashboard and Trend indicators into PFNs using a predefined linguistic–numerical scale:

$$\tilde{r}_{ij} = (\mu_{ij}^r, \eta_{ij}^r, \nu_{ij}^r), \tilde{t}_{ij} = (\mu_{ij}^t, \eta_{ij}^t, \nu_{ij}^t).$$

- Step 3. Integration of Dashboard and Trend information Aggregate the two PFNs into a single picture fuzzy evaluation:

$$\tilde{x}_{ij} = \alpha\tilde{r}_{ij} + (1-\alpha)\tilde{t}_{ij}.$$

- Step 4. Construction of the Picture Fuzzy Decision Matrix
  Form the PF decision matrix:

$$\tilde{X} = [\tilde{x}_{ij}]_{m\times n}.$$

- Step 5. PF-IBM aggregation. For each country A_i, aggregate SDG criteria using the weighted PF-IBM operator:

$$\tilde{S}_i = \left(\sum_{j \neq k} w_j \, w_k (\tilde{x}_{ij} \otimes \tilde{x}_{ik}) \right)^{1/2}.$$

- Step 6. Defuzzification and PF-IBM ranking. Compute the PF-IBM score:

$$\text{Score}(\tilde{S}_i) = \mu_i - \nu_i - \lambda \eta_i.$$

- Step 7. PF-CoCoSo robustness analysis. Normalize PF decision matrix values to obtain $\tilde{x}'_{ij}$.

- Step 8. Computation of additive and multiplicative utilities

$$S_i = \sum_{j=1}^{n} w_j \cdot \text{Score}(\tilde{x}'_{ij}),$$

$$P_i = \prod_{j=1}^{n} [\text{Score}(\tilde{x}'_{ij})]^{w_j}.$$

- Step 9. Calculation of CoCoSo compromise score

$$K_i = \lambda_c \left(\frac{S_i}{\max_i S_i} \right) + (1 - \lambda_c) \left(\frac{P_i}{\max_i P_i} \right).$$

- Step 10. PF-CoCoSo ranking and robustness evaluation Rank countries according to K_i. Compare PF-IBM and PF-CoCoSo rankings using rank correlation measures, top-k overlap, and sensitivity analysis with respect to λ_c.

Application And Findings

The empirical application of the proposed PF-IBM–PF-CoCoSo framework is conducted on European countries bordering the Mediterranean Sea by utilizing Sustainable Development Goal (SDG) Dashboard and Trend indicators. The application relies on three interrelated data components: (i) SDG Dashboard and Trend evaluations for each country–SDG pair, (ii) a picture fuzzy transformation scale for Dashboard indicators, and (iii) a picture fuzzy transformation scale for Trend indicators. These components jointly form the basis for constructing the picture fuzzy decision matrix and for subsequent aggregation and robustness analysis.

Table 1 presents the SDG Dashboard and Trend evaluations for the selected countries across SDG1–SDG17. For each country and SDG, the Dashboard indicator reflects the current achievement status (e.g., SDG achieved, challenges remain, major challenges remain), while the Trend indicator captures the recent direction of progress (e.g., on track, moderately improving, stagnating, decreasing). This dual representation enables the assessment to move beyond static SDG performance and incorporate dynamic progress information, which is essential for monitoring advancement toward the 2030 Agenda.

In Table 1, the SDG Dashboard and Trend indicators are expressed using specific abbreviations. For the Dashboard evaluations, SA (SDG Achieved) indicates that the respective goal has been largely achieved; CR (Challenges Remain) denotes that progress has been made but certain challenges persist; SCR (Significant Challenges Remain) reflects the presence of substantial barriers to achieving the goal; MCR (Major Challenges Remain) signifies severe and structural difficulties; and IU (Information Unavailable) indicates the absence of sufficient and reliable data for the corresponding goal.

Table 1. SDG Dashboard and Trend indicators for Mediterranean European countries (SDG1–SDG17).

SDG	BA	HR	CY	FR	GR	IT	ME	SI	ES	TR
SDG1	CR/ MI	SA/ OT	SA/ OT	SA/ OT	CR/ MI	CR/ MI	CR / MI	SA / OT	CR / MI	CR / MI
SDG2	SCR / MI	CR/ MI	SCR/ MI	CR/ MI	CR/ MI	CR/ MI	CR / MI	CR / MI	CR / MI	CR / MI
SDG3	CR/ MI	SA/ OT	CR/ MI	SA/ OT	SA/ OT	SA/ OT	CR / MI	SA / OT	SA / OT	CR / MI
SDG4	CR/ MI	SA/ OT	SA/ OT	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	SA/ OT	SA/ OT
SDG5	SCR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	SA/ OT	MCR / MI
SDG6	CR/ MI	SA/ OT	CR/ MI	SA/ OT	SA/ OT	SA/ OT	CR/ MI	SA/ OT	SA/ OT	CR/ MI
SDG7	CR/ MI	SA/ OT	CR/ MI	SA/ OT	CR/ MI	CR/ MI	CR/ MI	SA/ OT	SA/ OT	CR/ MI
SDG8	MCR / MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	MCR / MI
SDG9	SCR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	SCR/ MI	CR/ MI	CR/ MI	CR/ MI
SDG10	CR/ MI	SA/ OT	SA/ OT	CR/ MI	CR / MI	CR/ MI	CR/ MI	SA/ OT	CR/ MI	SCR/ MI
SDG11	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR / MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI
SDG12	MCR / MI	SCR/ DEC	MCR / DEC	MCR / MI	MCR / DEC	MCR / MI	IU/ IU	MCR / MI	MCR / MI	MCR / MI
SDG13	MCR / ST	MCR / ST	MCR / DEC	MCR / MI	MCR / MI	MCR / MI	MCR / MI	MCR / MI	MCR / MI	MCR / DEC
SDG14	IU/ IU	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI
SDG15	SCR/ MI	SCR/ MI	CR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI	SCR/ MI
SDG16	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	SCR/ MI
SDG17	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	CR/ MI	SA/ OT	CR/ MI	CR/ MI	CR/ MI

Source: Sustainable Development Report 2025)

Regarding the Trend indicators, OT (On Track) represents progress that is aligned with the target trajectory; MI (Moderately Improving) indicates a limited but positive improvement trend; ST

(Stagnating) denotes a lack of meaningful progress; and DEC (Decreasing) reflects a deterioration in performance over time.

To handle the inherent uncertainty, incompleteness, and qualitative nature of SDG indicators, Dashboard and Trend evaluations are transformed into Picture Fuzzy Numbers (PFNs). The linguistic categories used in the SDG Dashboard meaningfully differ in terms of achievement intensity and uncertainty. Accordingly, Table 2 reports the picture fuzzy transformation scale for Dashboard indicators. High achievement levels (e.g., SDG achieved) are represented by high membership degrees and very low non-membership degrees, whereas worsening performance categories (e.g., major challenges remain) are characterized by increased non-membership. Situations with insufficient information are modeled using balanced membership, neutrality, and non-membership values to reflect maximum uncertainty.

Table 2. Picture fuzzy transformation scale for SDG Dashboard indicators.

Dashboard status	μ	η	ν
SDG achieved (SA)	0.85	0.10	0.05
Challenges remain (CR)	0.60	0.30	0.10
Significant challenges remain (SCR)	0.35	0.45	0.20
Major challenges remain (MCR)	0.15	0.35	0.50
Information unavailable (IU)	0.33	0.33	0.34

Similarly, SDG Trend indicators describe the evolution of performance over time rather than the current status. Positive dynamics (on track or improving) and negative dynamics (stagnating or decreasing) convey different implications for future sustainability outcomes. Therefore, a separate picture fuzzy transformation scale is adopted for Trend indicators, as shown in Table 3. Positive trends are associated with higher membership degrees, while declining trends increase non-membership values. Trend unavailability is again represented by balanced picture fuzzy values to preserve neutrality.

Table 3. Picture fuzzy transformation scale for SDG Trend indicators.

Trend status	μ^t	η^t	ν^t
On track (OT)	0.80	0.15	0.05
Moderately improving (MI)	0.60	0.30	0.10
Stagnating (ST)	0.30	0.40	0.30
Decreasing (DEC)	0.10	0.30	0.60
Trend unavailable	0.33	0.33	0.34

Using the transformation scales in Tables 2 and 3, each Dashboard and Trend evaluation in Table 1 is converted into two PFNs for every country–SDG pair. These two PFNs are subsequently integrated into a single picture fuzzy assessment through a weighted linear combination, ensuring that both the current performance level and the progress trajectory contribute to the final evaluation. This process yields the integrated picture fuzzy decision matrix, which serves as the input for the PF-IBM aggregation.

Following the construction of the integrated picture fuzzy decision matrix, the next step of the analysis involves determining the relative importance of the SDG criteria. Since the Sustainable Development Goals differ in their systemic impact and urgency, treating all SDGs as equally important may obscure meaningful policy priorities. Therefore, this study adopts a transparent, theory-driven SDG prioritization scheme, explicitly aligned with the core principles of sustainable development.

The criterion weights were determined based on expert opinions. Within this framework, the Sustainable Development Goals (SDGs) were divided into three priority groups according to their relative importance levels derived from the final normalized weight values. This classification aims to reflect the systemic impacts of the goals on environmental sustainability, socio-economic stability, and development support mechanisms.

The first group comprises the Very High Priority SDGs and represents the system-dominant dimensions with the strongest impact on the overall sustainability assessment. In this group, SDG 12 (Responsible Production and Consumption) stands out with the highest weight value (0.3639), followed by SDG 7 (Accessible and Clean Energy) (0.1316) and SDG 9 (Industry, Innovation and Infrastructure) (0.1066). These goals are directly related to production structures, energy transition, and technological capacity, and are key drivers of sustainable development. High weight values indicate that performance differences in these areas are decisive in distinguishing the overall sustainability levels of countries.

The second group consists of High Priority SDGs and includes objectives directly related to basic needs, human well-being, and essential services. In this group, SDG 2 (End Hunger) (0.0958) and SDG 6 (Clean Water and Sanitation) (0.0702) reflect the critical importance of food security and access to basic services. Additionally, SDG 3 (Health and Quality of Life) (0.0422) and SDG 4 (Quality Education) (0.0442) are included as key elements strengthening human capital and societal resilience. While these objectives make a significant contribution to sustainability performance, their level of distinctiveness is more limited compared to the system-critical objectives in the first group.

The third group encompasses Medium Priority SDGs and consists of objectives related to social equity, environmental protection, urban development, and global cooperation. This group includes SDG 1 (Ending Poverty), SDG 5 (Gender Equality), SDG 8 (Decent Work and Economic Growth), SDG 10 (Reducing Inequalities), SDG 11 (Sustainable Cities and Communities), SDG 14 (Life Below Water), SDG 15 (Life on Land), SDG 16 (Peace, Justice and Strong Institutions), and SDG 17 (Partnerships for the Goals). While these goals are essential for long-term and inclusive development, their impact within the decision-making framework is mostly felt indirectly or through progress in higher-priority goals.

Based on this updated classification, numerical weights have been assigned to each SDG, ensuring that the sum of all criterion weights equals one. The resulting structure allows system-critical and highly distinctive SDGs to have a stronger impact on the final ranking, while also ensuring that the multifaceted scope of the 2030 Sustainable Development Agenda is preserved during the assessment process.

After applying these weights, each picture fuzzy evaluation was multiplied by its corresponding SDG weight, yielding a weighted picture fuzzy decision matrix. The PF-IBM operator was then employed to aggregate SDG-level information into a single country-level assessment. Unlike additive aggregation methods, PF-IBM explicitly accounts for interactions among criteria, thereby capturing the reality that progress in one SDG may reinforce or constrain progress in others. With parameters $p = q = 1$, the PF-IBM aggregation computes pairwise interactions among all SDGs, ensuring that highly weighted goals exert proportionally stronger influence throughout the aggregation process.

For each country, the PF-IBM operator produced three aggregated components—membership (μ_i), indeterminacy (η_i), and non-membership (ν_i)—representing overall sustainable development performance under uncertainty. These components were subsequently converted into a single scalar index using the score function $\text{Score}_i = \mu_i - \nu_i$, which rewards strong achievement while penalizing persistent opposition or failure. This score function is widely adopted in picture fuzzy decision-making studies due to its interpretability and robustness.

The updated PF-IBM results under the priority-based weighting scenario are summarized in Table 4.

Table 4. Updated PF-IBM Scores and Country Ranking

Rank	Country	μ_i	ν_i	PF-IBM Score
1	Spain (ES)	0.023151	0.004279	0.018872
2	Slovenia (SI)	0.023093	0.004298	0.018794
3	France (FR)	0.022814	0.004385	0.018428
4	Croatia (HR)	0.022510	0.004205	0.018305
5	Italy (IT)	0.021710	0.004750	0.016960
6	Türkiye (TR)	0.020125	0.005429	0.014696
7	Greece (GR)	0.019843	0.005231	0.014612
8	Cyprus (CY)	0.019082	0.005532	0.013550
9	Bosnia & Herzegovina (BA)	0.017181	0.005087	0.012094
10	Montenegro (ME)	0.014914	0.002902	0.012012

The findings reveal a clear stratification of sustainable development performance across the Mediterranean region. Countries occupying the top tier—Spain, Slovenia, France, and Croatia—exhibit relatively balanced achievement across high-weight SDGs, particularly those related to clean energy transitions, responsible production patterns, and institutional effectiveness. Their low non-membership values indicate fewer structural barriers across priority goals, allowing positive interactions to dominate the PF-IBM aggregation.

Turkiye's sixth-place ranking reflects its comparative strength, particularly in selected high-weighted Sustainable Development Goals (SDGs) such as SDG12 (Responsible Consumption and Production) and SDG7 (Clean Energy); recent progress in these areas compensates for weaker performance on governance and equity-related goals. The interactive nature of PF-IBM plays a decisive role here: progress on strategically weighted SDGs boosts Türkiye's overall score despite ongoing challenges in specific social dimensions. In contrast, Greece exhibits less positive trend dynamics on various environment-weighted goals, resulting in a marginal decline in its PF-IBM score despite similar underlying conditions. Lower-ranked countries such as Bosnia and Herzegovina and Montenegro are characterized by a concentration of major or significant challenges across multiple SDGs and limited positive trend signals. In these cases, PF-IBM penalizes inconsistent or fragmented progress, emphasizing the importance of consistency across goals rather than isolated successes. Overall, the extended results demonstrate that sustainable development performance in the Mediterranean context is shaped not only by levels of achievement but also by the appropriate distribution of progress among priority goals. When combined with scenario-based Sustainable Development Goals weighting, the PF-IBM framework offers a powerful and flexible decision support tool capable of revealing nuanced performance patterns under uncertainty. These findings provide a solid empirical basis for subsequent robustness analyses and policy-driven interpretations.

To assess the stability of the obtained country rankings against methodological assumptions, a comprehensive robustness analysis was conducted. In the multi-criteria decision-making literature, robustness refers to the extent to which rankings remain stable under reasonable variations in weighting schemes, indicator fusion, and aggregation operators. Given the multidimensional and uncertainty-prone nature of sustainable development assessment, such robustness analysis is essential to support the credibility and reliability of the findings.

First, the sensitivity of the rankings to the choice of aggregation method was examined. For this purpose, the country rankings obtained using the Picture Fuzzy Interactional Bonferroni Mean (PF-IBM) method were compared with those derived from the Picture Fuzzy CoCoSo (PF-CoCoSo) method, applied using the same picture fuzzy decision matrix and the same SDG weight vector. The association between the two rankings was measured using the Spearman rank correlation coefficient. Table 5 presents the rankings obtained by both methods along with the rank differences and their squared values.

Table 5. Comparison of PF-IBM and PF-CoCoSo Rankings and Rank Differences

Country	PF-IBM Rank	PF-CoCoSo Rank	d_i	d_i^2
Spain (ES)	1	1	0	0
Slovenia (SI)	2	2	0	0
France (FR)	3	4	−1	1
Croatia (HR)	4	3	1	1
Italy (IT)	5	5	0	0
Türkiye (TR)	6	6	0	0
Greece (GR)	7	7	0	0
Cyprus (CY)	8	8	0	0
Bosnia and Herzegovina (BA)	9	9	0	0
Montenegro (ME)	10	10	0	0
Total				2

Based on Table 5, the sum of squared rank differences is $\sum d_i^2 = 2$. For a sample of ten countries, the Spearman rank correlation coefficient was calculated as follows:

$$\rho = 1 - \frac{6\sum d_i^2}{m(m^2-1)} = 1 - \frac{6 \times 2}{10(10^2-1)} = 0.988.$$

This very high correlation coefficient indicates that the rankings obtained by PF-IBM and PF-CoCoSo are largely consistent, despite their different aggregation logics. The fact that the observed rank differences are limited to adjacent positions further confirms that the overall ranking structure is preserved and that the results are highly robust with respect to the choice of aggregation method.

As a second robustness dimension, the sensitivity of the results to the fusion parameter used to combine SDG Dashboard and SDG Trend indicators was examined. In the baseline analysis, both components were combined with equal importance ($\alpha = 0.50$). Two alternative scenarios were then considered: $\alpha = 0.30$, giving greater emphasis to trend dynamics, and α = 0.70, giving greater emphasis to current achievement levels. PF-IBM scores and rankings were recalculated for each scenario and compared with the baseline results. The Spearman rank correlation coefficients between the baseline and alternative scenarios are reported in Table 6.

Table 6. Rank Correlations under Alternative Dashboard–Trend Fusion Scenarios

Scenario Comparison	Spearman ρ
α = 0.50 vs. α = 0.30	0.88
α = 0.50 vs. α = 0.70	0.91

The correlation coefficients reported in Table 6 are both above the commonly accepted threshold of 0.80, indicating that the country rankings are only weakly sensitive to moderate changes in the relative importance assigned to current performance and progress trends. This finding suggests that the evaluation results are not driven by a specific fusion assumption.

To further examine ranking stability, the Average Rank Deviation (ARD) was computed. ARD measures the average absolute deviation of each country's rank from its mean rank across different scenarios. The ARD for each country was calculated using the following expression:

$$ARD_i = \frac{1}{K}\sum_{k=1}^{K} | r_i^{(k)} - \bar{r}_i |,$$

where $r_i^{(k)}$denotes the rank of country $i$under scenario k, $\bar{r}_i$is its mean rank across all scenarios, and $K$is the number of scenarios considered. The resulting ARD values are presented in Table 7.

Table 7. Average Rank Deviation (ARD) across Scenarios

Country	Mean Rank	ARD
Spain (ES)	1.00	0.00
Slovenia (SI)	2.00	0.00
France (FR)	3.00	0.33
Croatia (HR)	4.00	0.33
Italy (IT)	5.00	0.67
Türkiye (TR)	6.00	0.33
Greece (GR)	7.00	0.33
Cyprus (CY)	8.00	0.33
Bosnia and Herzegovina (BA)	9.00	0.33
Montenegro (ME)	10.00	0.00

As shown in Table 5, the average ARD across all countries is 0.42, indicating that country rankings vary by less than half a position on average across scenarios. Particularly low ARD values for the highest- and lowest-ranked countries suggest that the extreme performance groups remain stable under alternative methodological assumptions.

Robustness was also evaluated at the score level by computing the coefficient of variation for PF-IBM scores across scenarios. The average coefficient of variation was found to be below 6%, indicating limited dispersion in performance scores. This result demonstrates that not only ordinal rankings but also cardinal performance levels are relatively insensitive to reasonable methodological changes.

Overall, the combination of high Spearman rank correlations, low average rank deviations, and limited score variability provides strong quantitative evidence that the obtained country rankings are robust across different aggregation methods, Dashboard–Trend fusion schemes, and weighting assumptions. These findings confirm that the proposed picture fuzzy–based sustainable development assessment framework produces methodologically sound, stable, and reliable results, thereby offering a solid analytical basis for comparative sustainability analysis and policy-oriented interpretation.

Conclusion

This study proposed and applied an integrated picture fuzzy multi-criteria decision-making framework to evaluate the sustainable development performance of European countries bordering the Mediterranean. By jointly considering SDG Dashboard indicators, which reflect current achievement levels, and SDG Trend indicators, which capture recent progress dynamics, the analysis provided a temporally sensitive and uncertainty-aware assessment of national sustainability performance. The transformation of qualitative SDG information into Picture Fuzzy Numbers (PFNs) enabled the explicit modeling of achievement, hesitation, and opposition, thereby overcoming key limitations of conventional crisp and single-membership fuzzy approaches.

The methodological contribution of the study lies in the combined use of priority-based SDG weighting and the Picture Fuzzy Interactional Bonferroni Mean (PF-IBM) operator. Unlike traditional aggregation methods, PF-IBM explicitly incorporates interactions among criteria, allowing the evaluation framework to reflect the interdependent nature of the SDGs. In this context, progress or stagnation in highly interconnected goals propagates through the aggregation process, yielding a more realistic representation of sustainable development as a systemic phenomenon rather than a collection of isolated targets.

Empirical findings demonstrate that sustainable development performance among Mediterranean European countries exhibits clear differentiation patterns. Countries achieving balanced progress across high-priority environmental, social, and institutional SDGs consistently outperform those with fragmented or uneven performance profiles. The results confirm that sustainability leadership is not driven solely by success in individual goals, but rather by coherent and interaction-consistent advancement across multiple SDGs, a feature effectively captured by the PF-IBM framework.

The robustness analysis further strengthens the credibility of the findings. High Spearman rank correlation coefficients between PF-IBM and PF-CoCoSo rankings, limited sensitivity to alternative Dashboard–Trend fusion parameters, low average rank deviations, and small score variability collectively indicate that the results are stable across reasonable methodological variations. These outcomes suggest that the observed ranking patterns are driven by underlying performance structures rather than by specific modeling assumptions, thereby reinforcing the methodological reliability of the proposed framework.

From a methodological perspective, the study demonstrates that picture fuzzy modeling provides a powerful tool for SDG assessment under uncertainty, particularly when qualitative indicators and incomplete information dominate the evaluation landscape. The integration of interaction-aware aggregation and transparent SDG weighting offers a flexible yet rigorous decision-support structure that can be adapted to different regional contexts and policy priorities without compromising analytical consistency.

Despite its contributions, the study is subject to certain limitations. The analysis relies on aggregated SDG indicators at the national level and does not account for sub-national disparities or sector-specific dynamics. Moreover, while the priority-based weighting scheme enhances interpretability, alternative weighting approaches—such as data-driven or stakeholder-based methods—may yield complementary insights. Future research could extend the proposed framework by incorporating additional uncertainty models, longitudinal analysis, or hybrid weighting mechanisms, as well as by applying the methodology to other regions or thematic sustainability domains.

In conclusion, this study provides a robust, interaction-sensitive, and uncertainty-aware framework for comparative SDG performance assessment. The findings highlight the importance of integrated progress across interdependent goals and demonstrate the value of picture fuzzy methods in sustainability evaluation. The proposed approach offers both methodological advancement and practical relevance, making it a valuable contribution to the growing literature on multi-criteria sustainability assessment and evidence-based policy analysis.

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CHAPTER 9

FUZZY LOGIC FOR TRAFFIC STATE CLASSIFICATION

GİZEM ERDİNÇ[1]

Introduction

Indicating traffic breakdowns immediately has a pivot role in intelligent transportation engineering. Common approaches evaluate traffic condition by classifying traffic volume and average speed of vehicles in their binary-set-nature computation methods. These mathematical approaches are acceptable if they defined by precise and real-observed deterministic data. An effective mobility method needs to consider three factors as continuous traffic flow, traffic monitoring particularly at known traffic breakdown areas, and identifying and solving accident-related risk factors (Krause, Altrock, & Pozybill, 1996). For dealing with mentioned factors three parameters of traffic flow description are highlighted consisting of speed, density, and flow (Kalinic & Krisp, 2019) (Logghe & Immers, 2007). These parameters are macroscopic traffic model variables where aggregate traffic parameters or overall behaviour of the traffic

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stream are modelled. On the other hand, each traffic condition has some level of similarity, which makes traffic state division fuzziness. So, in this chapter the conception of ‘fuzziness’ is introduced as a better thinking than the current deterministic approaches with highlighting its advantages and easiness. However, traffic is known to be a highly complex system and drivers’ behaviour cannot be foreseen. In such circumstances, rather than ‘crisp’ mathematical models, fuzzy logic can be better performed beside their tractability in dealing with ambiguity and subjectivity are aligned with intelligent traffic modelling purposes in designing traffic breakdown-related alert or early warning systems, infrastructure and services planning, and sustainability development.

The Necessity of a Fuzzy Approach for Traffic State Modelling

The necessity of using reliable congestion detection and prediction techniques mostly arose from recent advancement in ITS. These techniques are categorized on two main levels: first, conventional methods formed on statistical approaches (e.g., autoregressive integrated moving average, Kalman filtering, etc.) joined with flow and congestion related parameters, second, data-driven methods employing such machine learning algorithms (e.g., artificial neural network, support vector regression, and fuzzy based computation) which these methods are the most frequent techniques in the latest research (Chmiel & Szwed, 2015) (Majumdar, Subhani, Roullier, Anjum, & R, 2021). Employing such techniques requires clarifying traffic congestion concepts. Although it has been investigated and developed in various aspects (Aftabuzzaman, 2007), among them all demand– capacity equilibrium is a significant characteristic of congestion that needs to be considered. This category is a relative calibre of traffic flow or a proportion of the best possible condition of the freeway and current condition which any change in equilibrium between traffic flow and approximate capacity of freeway can affect travel time, economic aspects, and variation of behaviour. Approximation plays a significant role in all traffic involved measurements; this means that each involved parameter in congestion respecting the precision of its representation in real-world circumstances needs to be analysed by a framework which can deal with ambiguity and uncertainty. Fuzzy inference methods can homogeneously approximate and model every existing continuous nonlinear system to a subjective degree of exactness (J.M., 1995). Describing level of traffic is connected to uncertainty associated properties, especially the traffic interval speed variable. Therefore, the computation of grading description of speed necessitates to be fuzzy. Among the first research (Pappis & Mamdani, 2007) proposed fuzzy inference-based method to deal with a specific problem of traffic congestion where a fuzzy based controller implemented in an intersection to compare the results with conventional vehicle-actuated controller, consequently, performed analyses indicated that fuzzy based controller has a preferable performance. There are many examples of solving complex traffic and transportation problems indicating the great potential of using fuzzy set theory techniques in literature, especially for congestion quantification (Erdinc, Colombaroni, & Fusco, 2023).

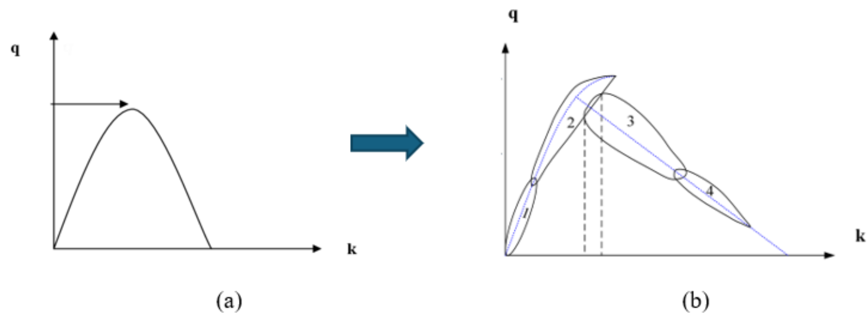
Traffic State Division

In the traffic engineering and management literature, three parameters are usually used to describe the traffic flow characteristic, which are volume of traffic (q = vehicle/h/km), speed (v = km/h) and traffic density (k = vehicle/km). The relationships among the 3 parameters can be expressed formally with the Equation 1 and the flow-density curve is given in Fig (1-a). The flow-density curve is called the traffic fundamental diagram.

$$Q=v\cdot k \tag{1}$$

Road traffic state refers to the real-time traffic flow condition of one road, but the road congestion definition is a vague concept, and it is difficult to use specific data to define. In general, the traffic condition of one road can be divided into different feature states. The traffic condition is divided into 4 features states as shown in Fig (1-b).

Fig 1. Traffic fundamental diagram (a) and traffic state division (b)



Kaynak: (Huang, Zhang, Liu, & Zhang, 2022)

The first state is freely driving state. Under this condition, flow and density are very low and speed is high. The vehicle can hardly be suffered from the influence of the vehicle ahead or behind of it and driver has good free driving degrees. The 2nd state corresponds to the steady-flow condition, in which both speed and flow remain at relatively high, but density is medium. Along with the increase of density, flow is on the increase and even can be increased to the traffic capacity. Under this traffic condition, the road infrastructure can get to be fully used, and driver can drive in larger freedom. The 3rd state is crowded flow state. Along with the increase of flow, speed falls sharply. The 4th state is serious crowded state. Here, the density is very high, and traffic jam often happens. The whole the road traffic condition is under the state of vehicle-following synchronization.

Table 1 summarizes all the states discussed above and presents the corresponding changes in the parameters as represented on the traffic fundamental and state division diagrams which is in given in Fig.1.

Table 1. Traffic state division summary

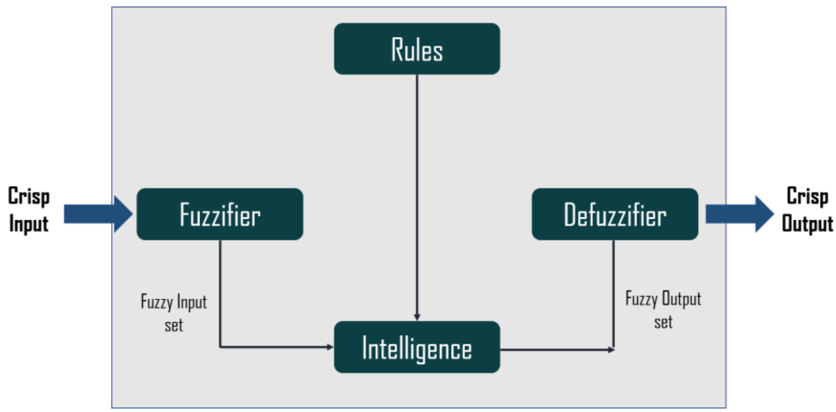
State	q	k	v
Freely driving -1-	Very low	Very low	High
Steady flow -2-	Very high	Medium	Very high
Crowded flow -3-	High	High	Low
Serious crowded -4-	Low	Very high	Very low

Therefore, with this summary, the state classification problem can be understood as a classified problem with three inputs (flow, density and speed) and one output (traffic congestion state). In this definition, all the variables are defined with linguistic definitions. While the traffic states are defined in classes between from freely driving to serious crowded; all the inputs variables clustered from very low, low, medium, high and very high.

Modelling Traffic States using Fuzzy Logic

The basic structure of a fuzzy-based system consists of three components, namely, fuzzification of the input variables, construct knowledge-based inference system and defuzzification of the output variable membership function (Fig.2).

Fig. 2. Fuzzy Logic architecture



Kaynak: (medium.com, 2025)

The first step is fuzzification which converts crisp input/output values into a set of fuzzy variables defined by membership functions. But before that, we specified both input and output parameters with their suitable numerical ranges which can give us a meaning to determine the impact of ranges on congestion and assigned linguistic variables corresponding to them. We defined three input parameters (Flow, Density, and Speed) and one out parameter (Traffic State). The input parameter – Flow – is assigned with the following linguistic variables: Very Low Flow (VLF), Low Flow (LF), Medium Flow (MF), High Flow (HF), and Very High Flow (VHF). The input parameter – Density – is clustered as: Very Low Density (VLD), Low Density (LD), Medium Density (MD), High Density (HD), Very High Density (VHD). The last input parameter -Speed is defined with three linguistic variables: Very Low Speed (VLS), Low Speed (LS), Medium Speed (MS), High Speed (HS), and Very High Speed (VHS). The output parameter – Traffic State – (calculated for each road section) is also fuzzified with five linguistic variables: Freely Driving (FD), Steady Flow (SF), Crowded Flow (CF), and Serious Crowded Flow (SCF).

After giving the variables linguistic definitions and numeric ranges, all of them fuzzified by assigning them membership functions. Fuzzy theory provides a basis for applying expert supervised customizations and rules, human knowledge has a central role in engineering and designing procedures (L.A., 1973). The most significant part of this idea is supporting and solving the crisp set limitations where dichotomizing (divide into two sharply defined parts) the individuals as members and non-members by increasing the volume of acceptable and allowable uncertainty through sacrificing some of the accurate information in favour of an ambiguous but more robust summary (Zadeh, 2015). The membership or non-membership of x value in the binary set A is assigned by function μA of A, illustrated by equation below (Erdinc, Colombaroni, & Fusco, 2023):

$$\mu_A(x) = \begin{cases} 1, if\ x \in A \\ 0, if\ x\ \notin A \end{cases} \tag{2}$$

As opposed to a crisp set in which a sharp and unambiguous distinction exists between the members and non-members, a fuzzy set introduces ambiguity with the aim at reducing complexity by eliminating the sharp boundary separating members of the set from non-members. Therefore, a value can partly be a participant of a specific set. These values are computed with linguistic metaphors rather than numerical expressions; an element is assigned in a class with membership function in closed interval 0 and 1; 1 expresses complete membership and 0 states non-membership; membership function μ_A quantifies the degree of belongingness of x to A. In the equation below the fuzzy set A is indicated:

$$A = \{x, \mu A(x) | x \in U\} \tag{3}$$

Even though there are various membership functions commonly used, in this paper triangular membership functions as given in Equation 2 are used since they capture the characteristics of the case study's fuzzy set and it's one of the most used examples.

$$\mu_A(x) = \begin{cases} 0,\ x < amin\ or\ x > amax \\ \frac{x - amin}{\beta - amin},\ x \in (amin, \beta) \\ \frac{amax - x}{amax - \beta},\ x \in (\beta, amax) \end{cases} \tag{4}$$

Fuzzy intelligence has been employed in various engineering and industrial applications. One of the first and popular fuzzy based control systems was introduced by Mamdani-Assilian [14]. The Mamdani fuzzy system has been commonly applied for dealing with complex problems in the field of traffic engineering (Kalinic & Krisp, 2019). This model employs fuzzy set instructions to convert a completely unstructured class of linguistic heuristics into an algorithm (Wang & Chen, 2014). The 'if-then' rule process of the Mamdani based algorithm (Fig. 2) is stated as: If x_i is A_{i1} and x_2 is A_{i2} and … x_r is A_{ir} then y is B_i (for i = 1, 2, …, k)

where x_i is the input variable and the output variable is y, A_{ir} and B_i are linguistic terms, and k is the number of rules.

As the second step and as the heart of the fuzzy model, we combine our previously fuzzified inputs using if–then fuzzy rules to build the inference and nonlinear surface model. Linguistic information (such as free flow and medium density) relates to AND operator meaning that minimum condition has to be met in order for conditional if statement to be fulfilled. All rules are evaluated in parallel based on fuzzy set theory that describes interpretation of the logical operations such as the complement, intersection, and union of sets. The consequent of each rule assigns an entire fuzzy set to the outputs. The fuzzy set is represented by a membership function to indicate the qualities of the consequent. Thus, every rule has a nonzero degree overlapping with other rules. The aggregation method is chosen to combine the inference results of these rules. Table 2 shows some of the rules. It is worth to remember here that all feasible points (even if they represent unstable conditions) need to be involved in Mamdani phase as rules to get a better model of q-k-v.

Table 2. Some examples of defined if-then rules

IF	THEN
If Flow is LF	Traffic is Smooth
If Density is VHD	Traffic is Stationary
If Flow is HF and Density is HD	Traffic is Queuing
If Flow is MF and Density is MD	Traffic is Slow
If Flow is HF and Density is VHD and Speed is MS	Traffic is Queuing
If Flow is LF and Density is LD and Speed is HS	Traffic is Intense

In determining fuzzy relations in the proposed model, applying proper composition techniques is a crucial step. Among various composition techniques 'max–min' is the most used (Ross, 2005). An illustration of a two-rule max-min composition in typical Mamdani inference mechanism is shown in Fig.2. This composition mathematically is stated as follows:

$$\mu_{CK}(Z) = \max \left[min\left[\mu AK(\text{input}(x)), \mu BK(\text{input}(y))\right]\right], K= 1, 2, \ldots, r \quad (5)$$

Where the membership functions are μ_{CK}, μ_{AK}, and μ_{BK} of output 'z' for rule 'k', input 'x', and 'y', respectively (Monjezi & Rezai, 2011).

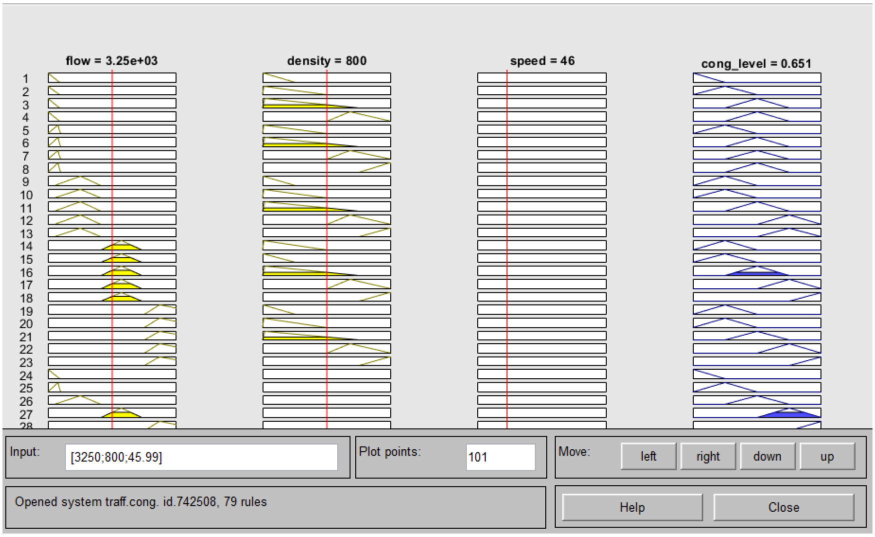
The defuzzification process is to convert each fuzzy output variable into a crisp (non-fuzzy) form. The centroid method is commonly used in the defuzzification process. The equation of centroid gravity method shown below:

$$Z_{COA}= \frac{\int \mu A(x)xdx}{\int \mu A(x)dx} \quad (6)$$

where 'z' is the fuzzy scheme output and aggregated output membership function is assigned as $\mu_A(z)$.

There are two ways to simulate the fuzzy logic system with the fuzzy logic toolbox: Rule viewer and Surface viewer. Each of them is a graphical user interface of the system. Each rule is a row of plots, and each column is a variable. The rule numbers are displayed on the left of each row. Each column here shows the set of membership functions for a particular input. So, in this example, there are 79 membership functions for each input (flow, density and speed), and similarly 79 membership functions for traffic congestion state output. The plot in the output column shows how to rules have applied to the output variable, the bottom output plot shows how to output of each rule is combined to make an aggregate output in the fuzzified value. The red line on the output variable provides the defuzzied value of speed limit which is an answer. For in this example, Fig. 3 shows of the observation that if real-time input parameters properties are entered as: flow = 3250 veh/h/km, density = 800 veh/km and speed = 46 km/h then the congestion level would be forecasted as 0.651 which is categorized as Crowded Flow State (3). The obtained results illustrate that the proposed fuzzy inference system is quite efficient to generalize nonlinear complex relations between levels of congestion and the other numerical properties of traffic.

Fig 3. Rule viewer scheme

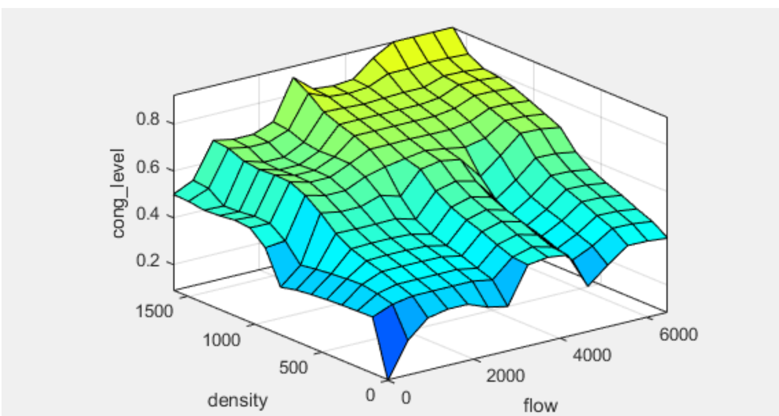


Conclusion

Estimating the level of congestion carried out was based on both historic and real-time observations which play a significant role in various traffic models (Erdinc, Colombaroni, & Fusco, 2023). Instead of conventional methods of traffic detection, the proposed model has a sophisticated discipline known as approximate reasoning (Falcone, Lima,, & Martinelli, 2020), (Pradeepkumar & Ravi, 2018) through which exact traffic connected properties (e.g., geometric features including junctions, bifurcations, off-ramps, and on-ramps) that can be assigned in microscopic and mesoscopic types of traffic modelling (Imran, Khan, Gulliver, Khattak, & Nasir, 2020) are sacrificed to reach significantly low time and computational efforts. Besides, natural linguistic rules are forming the executed model, which is aligned with the general concepts of traffic characteristics. Also, because of employing multiple and compound rules in the modelled inference system instead of using a single rule, the results obtained from a combined description of the congestion state.

One of the most noteworthy contributions of the simulated results is fuzzy surface view which can construct advantageous information extracted from the analysed system's data, for example, evaluating correlation and strength of the relationship between assigned input and output variables. The close relationship between both Flow, Density and Congestion Level variables of the example is given in figure 4. The most intense fluctuation occurs in the congestion level when flow is between 4000-6000 vehicles and density is 500-1100 vehicles. Also, when in the cases of flow are in the range of 1000-2000 and more than 6000 vehicles congestion level is increased around 50% with increasing of density rate.

Fig. 4. Surface viewer scheme of the relationship between congestion level-flow-density



Although provided information by fuzzy surface view mainly focuses on the input-output variables correlations, another feature of the provided view is about the system reaction rate to the fluctuations caused by input variables and the direction of alterations effects on the output variable. It is a significant advantage, since a completely different effectual view of the analysed system coupled with having the capability to evaluate many possible scenarios and outcomes at once can be observed by engineers without having to infer the system's mathematical formulations where conventional control models disable to provide.

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CHAPTER 10

A MULTI-CRITERIA COMPARATIVE ANALYSIS OF FOOD SECURITY PERFORMANCE IN THE EUROPEAN UNION COUNTRIES AND TÜRKİYE

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Introduction

Food security is a complex concept that goes beyond the mere production of sufficient quantities of food and encompasses multidimensional aspects such as economic accessibility, stability of food supply, nutritional quality, environmental sustainability, and resilience to crises (Matkovski et al., 2020). At the global level, population growth, climate change, economic fluctuations, post-pandemic vulnerabilities, and increasing geopolitical risks have made differences in countries' food security performance more visible. In this context, the comparative evaluation of countries' food security levels has become a critical necessity for policymakers and

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international organizations alike (Mazzocchi, Ragona, & Zanoli, 2013).

In the literature, countries' food security performance is most commonly monitored through the Global Food Security Index (GFSI) and the multidimensional indicator frameworks proposed by the Food and Agriculture Organization of the United Nations (FAO) (FAO, 2025a). These indices provide a comprehensive framework covering the core dimensions of food security—such as affordability, availability, quality and safety, and sustainability—and thus constitute an important reference point for cross-country comparisons (Izraelov & Silber, 2019). However, as these indices are largely based on composite scores, the analytical disentanglement of the relative importance of individual indicators and their specific contributions to country rankings remains limited. Due to the structure of composite indices, strong performance in certain dimensions may compensate for weaknesses in others, making it difficult to clearly identify which criteria play a more decisive role in shaping overall country performance. From this perspective, multidimensional evaluation problems such as food security—which simultaneously involve economic, environmental, structural, and governance-related dimensions—can inherently be addressed as Multi-Criteria Decision-Making (MCDM) problems. MCDM approaches enable the holistic evaluation of multiple and often conflicting criteria within a single decision framework, the systematic determination of priority relationships among criteria, and the transparent ranking of alternatives (Özkaya & Özkaya, 2023). The use of MCDM methods in country-level food security comparisons goes beyond merely identifying countries' positions in a ranking; it also enhances analytical consistency and interpretability by explicitly revealing the contributions of individual criteria to the final decision outcomes (Rouyendegh & Savalan, 2022).

In this section, countries' food security performance is conceptualized as an MCDM problem, and cross-country comparisons are conducted by taking the relative importance of criteria into account. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), one of the MCDM methods, is employed to rank countries' food security performance. TOPSIS is a classical yet effective method that ranks alternatives based on their relative distances from ideal and anti-ideal solutions and is widely preferred in the literature due to its ease of application and the clarity of its results (Chakraborty, 2022). The analysis covers European Union (EU) countries, including Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden, along with the United Kingdom and Türkiye. This sample structure allows for a comparative examination of relative performance differences among EU countries and Türkiye's position within this structure under a unified methodological framework.

The criteria used in the analysis are designed to represent multiple dimensions of food security. Accordingly, gross domestic product (GDP) per capita, food supply variability, food price anomaly indicators, net import dependency in agriculture and livestock, the share of agriculture in government expenditures, energy production from biofuels, organic fertilizer use, pesticide use, the cost of a healthy diet, the proportion of the population unable to afford a healthy diet, water stress levels, agricultural emission intensity, the value added of the agriculture–forestry–fisheries sector, and agricultural land area—considered through selected ratios—are included. This set of criteria is structured to jointly reflect the dimensions of economic accessibility, production capacity, external dependency, public policy support, environmental pressures, and sustainable resource use in food security. The relative weights of the criteria are determined based on evaluations provided by expert decision-makers. In the first stage, all criteria are included in the weighting process and countries are ranked accordingly. In the second stage, several criteria representing environmental and sustainability dimensions are excluded from the analysis, and experts are asked to reassess the remaining criteria. The impact of this modification on country rankings is then examined comparatively. This two-stage structure allows for an analytical assessment of the determining role of sustainability-related dimensions in shaping country rankings.

In the final section of the study, the resulting country rankings and criterion effects are evaluated through comparison with the overall GFSI rankings. While the study is grounded in the multidimensional food security framework proposed by the FAO, it offers an analytical approach that more explicitly reveals the relative importance of criteria and their effects on country rankings. In this respect, the study serves as a complementary assessment to existing index-based evaluations and aims to produce more interpretable and decision-oriented outputs for policymakers.

Method

Due to its multidimensional nature, food security requires the simultaneous consideration of criteria measured on different scales and often exerting effects in different directions within a single decision framework. In this respect, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, which enables the ranking of countries based on their relative closeness to ideal and anti-ideal solutions while explicitly incorporating criterion weights, is adopted as an analytical tool consistent with the objectives of this study. Owing to both the interpretability of its results and the analytical consistency it provides in cross-country comparisons, TOPSIS offers a suitable decision-support framework for evaluating food security performance. The steps of the method are outlined below (Sharaf, 2023).

Step 1. Construction of the decision matrix: First, a decision matrix $D=\left[A_{ij}\right]_{n\times m}$, consisting of n alternatives and m criteria, is constructed. Here, A_{ij} represents the value of the i-th alternative with respect to the j-th criterion.

Step 2. Determination of criterion weights: Assuming that not all criteria are of equal importance, weights are assigned to each criterion. Decision-makers determine a set of weights reflecting the relative importance of each criterion. The weight vector is defined as $W=[w_1, w_2, \ldots, w_m]$, subject to the conditions $w_j > 0$ and $\sum_{j=1}^{m} w_j = 1$.

Step 3. Normalization of the decision matrix: Since criteria may be measured in different units, the decision matrix must be transformed into a dimensionless form. The normalized decision matrix D_N is defined by Equation (1), where each normalized value r_{ij} is calculated using Equation (2):

$$D_N=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{1}$$

$$r_{ij} = \frac{A_{ij}}{\sqrt{\sum_{i=1}^{n} A_{ij}^2}} \tag{2}$$

Step 4. Construction of the weighted normalized decision matrix: At this stage, each normalized criterion value is multiplied by its corresponding weight to obtain the weighted normalized decision matrix, denoted as D_{NW} and defined by Equation (3):

$$D_{NW} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1m} \\ v_{21} & v_{22} & \cdots & v_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ v_{n1} & v_{n2} & \cdots & v_{nm} \end{bmatrix} \tag{3}$$

For $1 \leq i \leq n$ and $1 \leq j \leq m$, each element v_{ij} is computed as:

$$v_{ij} = w_j r_{ij} \tag{4}$$

Step 5. Determination of positive and negative ideal solutions: In this step, the positive ideal solution (v^+) and the negative ideal solution (v^-) are identified for each criterion. The positive ideal solution consists of the maximum values for benefit criteria (C_b) and the minimum values for cost criteria *(C_c)*, whereas the negative ideal solution is defined conversely. The positive and negative ideal solution vectors are calculated as follows:

$$v^+ = \left\{ \max_i v_{ij} \,\middle|\, j \in C_b;\ \min_i v_{ij} \,\middle|\, j \in C_c \right\}, \quad j=1, 2, \ldots, m \tag{5}$$

$$v^- = \left\{ \min_i v_{ij} \,\middle|\, j \in C_b;\ \max_i v_{ij} \,\middle|\, j \in C_c \right\}, \quad j=1, 2, \ldots, m \tag{6}$$

Step 6. Calculation of distance measures: At this stage, the distances of each alternative from the positive and negative ideal solutions are calculated using the Euclidean distance metric. The distance to the positive ideal solution S_i^+ and the distance to the negative ideal solution S_i^- are computed using Equations (7) and (8), respectively:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v^+\right)^2} \tag{7}$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v^-\right)^2} \tag{8}$$

These distances indicate how far each alternative is from the ideal and anti-ideal solutions across all criteria.

Step 7. Calculation of the relative closeness to the ideal solution: The relative closeness of each alternative to the positive ideal solution, denoted by R_i, is calculated as the ratio of its distance from the negative ideal solution to the total distance, as shown in Equation (9):

$$R_i = \frac{S_i^-}{S_i^+ + S_i^-}, \quad i = 1,2,\ldots,n \tag{9}$$

The value of R_i lies between 0 and 1; values closer to 1 indicate greater proximity to the positive ideal solution, while values closer to 0 indicate greater proximity to the negative ideal solution.

Step 8. Ranking of alternatives: In the final step, alternatives are ranked based on their R_i values. The preference order is established by sorting alternatives in descending order of R_i.

Data Set and Criteria Construction

In this study, food security is conceptualized as a multidimensional structure that extends beyond the mere physical availability of food to jointly encompass economic accessibility, nutritional quality, environmental sustainability, and external dependency. Accordingly, the constructed dataset consists of indicators capable of reflecting both the current performance of countries' food systems and their medium- and long-term vulnerabilities. All data used in the study were obtained from the FAOSTAT database to ensure international comparability and data consistency (FAO, 2025b).

In selecting the criteria, widely accepted dimensions of food security in the literature were taken into consideration, and variables representing economic welfare, agricultural production capacity, environmental pressures, and access to nutrition were jointly evaluated. Within this framework, the ratio of energy production from biofuels to agricultural production, GDP per capita, the share of public expenditures allocated to the agricultural sector, the share of agricultural value added in GDP, and the ratio of agricultural land area to population were treated as maximization-oriented indicators reflecting countries' production capacity and economic resilience. In contrast, food supply variability, food price anomalies, pesticide use, water stress levels, emission intensity per unit of agricultural production, and indicators representing economic and social constraints on access to healthy diets were evaluated as minimization-oriented criteria. To eliminate scale differences among countries and enhance comparability, ratio-based indicators were used to a large extent instead of absolute values. Particularly in countries with heterogeneous structures in terms of agricultural output, land area, population, and economic size, the use of ratios increases the representational power of indicators and allows for a more robust interpretation of the results. For instance, the ratio of energy production from biofuels to agricultural production reveals the renewable energy and bioeconomy potential of the agricultural sector, while the ratio of organic fertilizer use to agricultural land area reflects the prevalence of sustainable agricultural practices. Similarly, the share of agricultural value added in GDP and the ratio of agricultural land area to population indicate the strategic importance of agriculture within the economic structure and the long-term food production capacity. From a food security perspective, external dependency emerges as a critical source of vulnerability, particularly during periods characterized by global supply shocks and price volatility. Therefore, net import dependency indicators for both the agricultural and livestock sectors were additionally calculated in this study. Net import dependency was derived by dividing the difference between imports and exports by total supply and is formulated as shown in Equation (10). This indicator relatively captures the capacity of domestic production to meet internal demand and the impact of trade structures on food security. Since higher values indicate greater reliance on imports and thus increased exposure to external shocks, net import dependency in both agriculture and livestock sectors was incorporated into the model as a minimization-oriented criterion.

$$\text{net import dependency}=\frac{\text{Imports-Exports}}{\text{Total supply}} \tag{10}$$

Table 1 Criteria, Units, Optimization Directions, and Data Years

Criterion	**Direction**	**Unit**	**Data Year**
GDP per capita	Max	US dollars per capita (current prices)	2023
Share of agriculture in government expenditure	Max	Percentage (%)	2023
Food price anomaly indicator	Min	Index	2022
Value added (agriculture, forestry, and fisheries) / GDP	Max	Percentage (%)	2024
Cost of a healthy diet	Min	Purchasing power parity (PPP) dollars per capita per day	2024
Food supply variability	Min	Kilocalories per capita per day	2023
Net import dependency in livestock	Min	Ratio	2023
Net import dependency in agriculture	Min	Ratio	2023
Population unable to afford a healthy diet / total population	Min	Ratio	2024
Agricultural land area / population	Max	Hectares per capita	2023
Water stress level	Min	Percentage (%)	2022
Organic fertilizer use / agricultural land area	Max	Kilograms per hectare	2023
Pesticide use	Min	Kilograms per hectare	2023
Energy production from biofuels / agricultural production	Max	Terajoules per ton	2023
Agricultural emissions / value of agricultural production	Min	Kilotons per 1,000 US dollars	2023

Finally, recognizing that food security is not limited solely to production and trade dimensions, indicators such as the cost of a healthy diet and the proportion of the population unable to afford a healthy diet were included in the dataset. These variables reflect economic and social access to nutritious and healthy food beyond mere physical availability, thereby strengthening the human dimension of food security. All criteria were evaluated within the TOPSIS framework in accordance with their specified optimization directions, and countries' food security performance was analyzed from a holistic perspective. The criteria used in the study, along with their units, optimization directions, and data years, are summarized in Table 1.

Determination of Criteria Weights

The relative importance levels of the criteria used in the study were determined in a manner that reflects the multidimensional nature of food security. The weighting process was conducted based on the joint evaluations of three decision-makers with domain expertise, and the final set of criteria weights was obtained through consensus by reconciling individual judgments.

An examination of the weight values indicates that the highest weights were assigned to GDP per capita (0.15), agricultural value added as a share of GDP (0.10), and agricultural land area per capita (0.10). This distribution suggests that economic capacity, the relative importance of the agricultural sector within the national economy, and per capita production resources play a decisive role in shaping countries' food security performance. The criteria representing the economic access dimension—namely the cost of a healthy diet (0.08) and the proportion of the population unable to afford a healthy diet (0.07)—account for a substantial share of the total weight. This finding highlights that food security is not determined solely by production volumes, but is also directly linked to individuals' effective access to healthy and balanced diets.

Table 2 Conceptual Groups of Criteria and Weight Distribution

Criterion Group	Criterion	Weight
Economic Welfare and Access	GDP per capita	0.15
	Cost of a healthy diet	0.08
	Population unable to afford a healthy diet / total population	0.07
Food Supply and Market Stability	Food supply variability	0.08
	Food price anomaly indicator	0.07
Agricultural Structure and External Dependency	Net import dependency in agriculture	0.06
	Net import dependency in livestock	0.05
	Value added (agriculture, forestry, and fisheries) / GDP	0.10
	Agricultural land area / population	0.10
Sustainability	Agricultural emissions / value of agricultural production	0.04
	Pesticide use	0.04
	Organic fertilizer use / agricultural land area	0.04
	Energy production from biofuels / agricultural production	0.02
Resource Availability and Production Continuity	Water stress level	0.06
Public Policies	Share of agriculture in government expenditure	0.04

Within the food supply and stability dimension, food supply variability (0.08) and the food price anomaly indicator (0.07) reflect the system's vulnerability to price and supply shocks. The relatively high weights assigned to these criteria indicate that the pressures exerted by price fluctuations and supply uncertainties on food security are explicitly taken into account in the analysis. In the environmental and sustainability dimension, agricultural emission intensity (0.04), pesticide use (0.04), and organic fertilizer use (0.04) are represented by lower but balanced weights. This allocation demonstrates that while environmental factors may not carry as much weight as short-term food accessibility, they are nevertheless integrated into the model as indispensable components for long-term food security and the sustainability of agricultural systems. Finally, the relatively low weight assigned to the ratio of energy production from biofuels to agricultural production (0.02) indicates that food–energy competition is treated as a secondary yet complementary risk factor in the study, whereas the primary determinants of food security performance are economic and structural variables. Overall, the resulting weight set reflects the economic, social, environmental, and structural dimensions of food security in a balanced manner and is structured to prevent any single dimension from disproportionately dominating the results. These weights are subsequently employed in the weighting stage of the TOPSIS method, enabling a holistic evaluation of countries' food security performance.

Results

Within the scope of the analysis, countries' distances to the positive ideal solution (S_i^+), distances to the negative ideal solution (S_i^-), and the relative closeness coefficients (R_i) calculated based on these distances were determined as presented in Table 3. Higher values of R_i indicate that the corresponding country is closer to the ideal food security profile, and the final ranking of countries was established accordingly based on these values.

Table 3 Food Security Performance of Countries Based on TOPSIS Results

Countries	S_i^+	S_i^-	R_i	**Ranking**
Austria	0.0656	0.0969	0.5964	6
Belgium	0.0742	0.0958	0.5633	12
Bulgaria	0.0856	0.0942	0.5240	20
Croatia	0.0835	0.0867	0.5095	23
Cyprus	0.0917	0.0768	0.4557	28
Czechia	0.0753	0.0959	0.5600	13
Denmark	0.0593	0.1004	0.6289	3
Estonia	0.0713	0.1011	0.5865	8
Finland	0.0641	0.0989	0.6067	4
France	0.0688	0.0960	0.5827	9
Germany	0.0761	0.0893	0.5399	17
Greece	0.0807	0.0856	0.5149	22
Hungary	0.0842	0.0931	0.5253	19
Ireland	0.0446	0.1105	0.7123	1
Italy	0.0793	0.0859	0.5200	21
Latvia	0.0730	0.1049	0.5896	7
Lithuania	0.0747	0.1009	0.5746	10
Luxembourg	0.0578	0.1147	0.6648	2
Malta	0.1193	0.0490	0.2913	29
Netherlands	0.0657	0.1004	0.6043	5
Poland	0.0776	0.0962	0.5535	14
Portugal	0.0834	0.0810	0.4927	26
Romania	0.0945	0.0856	0.4752	27
Slovakia	0.0862	0.0838	0.4930	25
Slovenia	0.0778	0.0927	0.5438	15
Spain	0.0754	0.0877	0.5379	18
Sweden	0.0713	0.0925	0.5645	11
Türkiye	0.0862	0.0890	0.5078	24
United Kingdom	0.0750	0.0894	0.5437	16

An examination of the results presented in Table 3 reveals pronounced differences in food security performance across countries. According to the findings, Ireland ranks first with the highest relative closeness coefficient (R_i=0.7123), followed by Luxembourg (0.6648) and Denmark (0.6289). The strong performance of these countries can be attributed to their robust economic structures, high value added in the agricultural sector, relatively low levels of external dependency, and more favorable conditions in terms of access to healthy diets. In particular, the fact that Ireland and Luxembourg exhibit relatively large distances from the negative ideal solution (S_i^-) and relatively small distances from the positive ideal solution (S_i^+) indicates that these countries display a balanced and strong performance across the selected criteria. An analysis of the top ten countries shows a clear predominance of Northern and Western European countries. Countries such as Finland, the Netherlands, Austria, Estonia, Latvia, and France exhibit comparatively favorable values in terms of economic stability, agricultural production efficiency, and food access indicators. This outcome can be explained by the effective allocation of resources to agriculture and food systems within public policies, as well as the relatively balanced performance achieved in environmental and nutritional indicators. Countries positioned in the middle of the ranking include Germany, Poland, Slovenia, Spain, and the United Kingdom. Although these countries perform strongly in certain criteria, they are unable to attain higher rankings due to relative disadvantages in indicators such as food price stability, environmental pressures, or net import dependency. This finding underscores that food security performance is not determined by success in a single dimension, but rather by the balance achieved across multiple dimensions. An examination of the lower-ranked countries indicates that Malta, Cyprus, Romania, Slovakia, and Türkiye exhibit lower R_i values. The lower performance of these countries can be associated with structural factors such as limited agricultural land relative to population size, higher levels of external dependency, water stress, and food price volatility. Türkiye ranks

24th with an R_i value of 0.5078 and is positioned within the lower-middle performance group. Despite Türkiye's potential in terms of agricultural production capacity and land availability, its overall performance is constrained by vulnerabilities observed in indicators such as food price anomalies, water stress levels, and environmental pressures arising from agricultural production. This suggests that, for Türkiye, food security policies should prioritize price stability, resource efficiency, and environmental sustainability rather than focusing solely on increasing production levels.

Table 4 Updated Criteria Weights

Criterion Group	**Criterion**	**Weight**
Economic Welfare and Access	GDP per capita	0.1744
	Cost of a healthy diet	0.0930
	Population unable to afford a healthy diet / total population	0.0814
Food Supply and Market Stability	Food supply variability	0.0930
	Food price anomaly indicator	0.0814
Agricultural Structure and External Dependency	Net import dependency in agriculture	0.0698
	Net import dependency in livestock	0.0581
	Value added (agriculture, forestry, and fisheries) / GDP	0.1163
	Agricultural land area / population	0.1163
Resource Availability and Production Continuity	Water stress level	0.0698
Public Policies	Share of agriculture in government expenditure	0.0465

At this stage, an alternative scenario was constructed by excluding sustainability-related criteria representing environmental and long-term effects—namely pesticide use, organic fertilizer use, agricultural emission intensity, and energy production from biofuels—from the analysis. The primary objective of this approach is to observe the extent to which countries' food security performance changes when the sustainability dimension is excluded. Following the removal of sustainability criteria, the weights of the remaining criteria were normalized, and the resulting values are presented in Table 4.

The rankings obtained under this scenario are presented in Table 5.

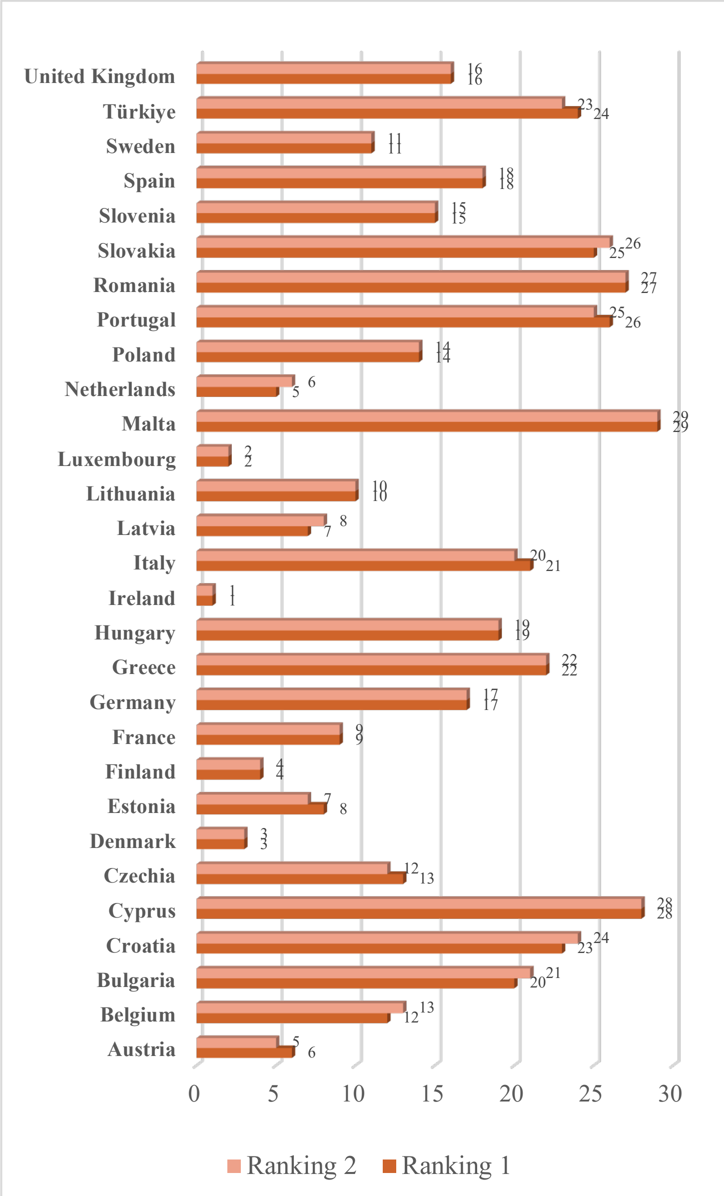
Graph 1 visually illustrates the ranking differences between the two scenarios and clearly demonstrates which countries are positively or negatively affected by this change. An examination of Figure 1 indicates that, for the majority of countries, rankings are either preserved or exhibit only marginal changes of one position. This finding suggests that the food security performance model employed in the study maintains its overall structure even when sustainability criteria are excluded, and that the results are not excessively sensitive to any single group of criteria. adjustments indicate that sustainability criteria play a secondary and balancing role in the overall food security performance of these countries, without fundamentally altering their relative positions.

In particular, the results for top-ranked countries are highly consistent across both scenarios. Ireland retains its first-place position in both rankings, demonstrating that its food security performance remains strong regardless of the inclusion of sustainability-related criteria.

Table 5 Food Security Rankings of Countries Excluding Sustainability Indicators

Countries	S_i^+	S_i^-	R_i	**Ranking**
Austria	0.0713	0.1097	0.6060	5
Belgium	0.0833	0.1080	0.5646	13
Bulgaria	0.0948	0.1050	0.5256	21
Croatia	0.0936	0.0954	0.5046	24
Cyprus	0.1023	0.0870	0.4595	28
Czechia	0.0825	0.1082	0.5673	12
Denmark	0.0651	0.1120	0.6324	3
Estonia	0.0766	0.1144	0.5991	7
Finland	0.0692	0.1114	0.6167	4
France	0.0747	0.1083	0.5917	9
Germany	0.0848	0.1006	0.5427	17
Greece	0.0886	0.0950	0.5174	22
Hungary	0.0932	0.1042	0.5279	19
Ireland	0.0450	0.1262	0.7370	1
Italy	0.0872	0.0974	0.5274	20
Latvia	0.0793	0.1184	0.5989	8
Lithuania	0.0813	0.1136	0.5829	10
Luxembourg	0.0611	0.1308	0.6817	2
Malta	0.1335	0.0548	0.2908	29
Netherlands	0.0738	0.1118	0.6024	6
Poland	0.0862	0.1084	0.5570	14
Portugal	0.0923	0.0906	0.4953	25
Romania	0.1057	0.0944	0.4719	27
Slovakia	0.0957	0.0934	0.4938	26
Slovenia	0.0858	0.1050	0.5504	15
Spain	0.0828	0.0982	0.5424	18
Sweden	0.0778	0.1034	0.5706	11
Türkiye	0.0949	0.0997	0.5123	23
United Kingdom	0.0829	0.1008	0.5489	16

Graph 1 Comparison of Rankings



Similarly, Luxembourg (2nd), Denmark (3rd), and Finland (4th) maintain their positions in both scenarios. The persistence of these countries at the top of the rankings can be attributed to their strong economic capacity, high agricultural productivity, and stable food supply structures, which allow them to sustain superior performance even when environmental sustainability factors are excluded. Changes observed among mid-ranked countries are relatively limited and generally confined to shifts of ±1 position. For instance, Austria (6→5), Czechia (13→12), and Estonia (8→7) move up by one position, while Belgium (12→13), Latvia (7→8), and the Netherlands (5→6) each drop by one position. These minor rank. A similar pattern is observed for lower-ranked countries. Countries such as Malta (29th), Cyprus (28th), Romania (27th), and Greece (22nd) maintain their positions across both scenarios. This suggests that, for these countries, the primary determinants of food security performance are factors such as economic access, agricultural structure, and external dependency rather than environmental sustainability. With specific reference to Türkiye, a marginal improvement is observed, with the country moving from 24th to 23rd place. This finding indicates that Türkiye's relative performance improves slightly when sustainability criteria are excluded, implying that environmental and resource-related constraints exert a limiting effect on its overall food security performance. However, the fact that this improvement is limited to a single rank underscores that Türkiye's food security performance is shaped not only by environmental factors but also by structural and economic determinants. Overall, the high degree of consistency between the two rankings demonstrates that the study's results are methodologically robust, resilient to sensitivity analysis, and well suited to generating policy-relevant insights. The inclusion or exclusion of sustainability-related criteria does not fundamentally alter countries' relative positions; rather, it enhances the visibility of the dimensions driving performance for certain countries. Similar analyses may also be conducted for other dimensions.

Comparison of the Results with the Overall GFSI Rankings

The country rankings obtained in this study are comparatively evaluated against the results of the Global Food Security Index (GFSI), one of the most widely used global indicators in the field of food security (GFSI, 2022). However, before conducting this comparison, it is necessary to clearly emphasize the differences in scope and methodology between the two approaches. The GFSI covers a total of 113 countries and does not include Croatia, Cyprus, Estonia, Latvia, Lithuania, Luxembourg, and Malta. In contrast, since the present study considers all European Union member states, these countries are also included in the analysis. The inclusion of countries that fall outside the scope of the GFSI allows for a more comprehensive and homogeneous assessment of food security performance, particularly with respect to comparisons between EU countries and Türkiye. As shown in Table 6, although the numerical coverage of the rankings differs, a high degree of consistency is observed between the results obtained in this study and the overall GFSI rankings. Although one ranking is based on 29 countries and the other on 21 countries, the relative positions of countries are largely preserved. This finding indicates that the MCDM approach employed and the selected set of criteria are capable of producing results that are consistent with a globally recognized index. Nevertheless, the comparative assessment highlights two countries in particular—the United Kingdom and Portugal—as exhibiting notable discrepancies. This divergence may stem from the inclusion of governance, policy framework, and qualitative indicators in the GFSI methodology, whereas the present study adopts a framework that relies more heavily on quantitative and structural variables. Overall, the comparison with the GFSI demonstrates that the results of this study are not arbitrary, but rather largely aligned with a globally accepted index. At the same time, the differences observed for certain countries illustrate that food security rankings may vary depending on which dimensions of food security are emphasized, thereby confirming that this study offers a complementary perspective to existing index-based assessments.

Table 6 Comparison of the Results with the Overall GFSI Rankings

Country	**TOPSIS Ranking**	**GFSI (2022)**
Austria	6	8
Belgium	12	11
Bulgaria	20	16
Croatia	23	-
Cyprus	28	-
Czechia	13	10
Denmark	3	9
Estonia	8	-
Finland	4	1
France	9	3
Germany	17	12
Greece	22	17
Hungary	19	18
Ireland	1	2
Italy	21	15
Latvia	7	-
Lithuania	10	-
Luxembourg	2	-
Malta	29	-
Netherlands	5	4
Poland	14	14
Portugal	26	7
Romania	27	20
Slovakia	25	19
Slovenia	15	-
Spain	18	13
Sweden	11	5
Türkiye	24	21
United Kingdom	16	6

Conclusions and Policy Implications

In this study, the food security performance of European Union countries and Türkiye was comparatively evaluated using the TOPSIS approach. Within the scope of the analysis, indicators representing multiple dimensions—such as economic accessibility, supply and price stability, agricultural structure, and production capacity—were jointly considered, while the contribution of sustainability-related criteria was examined through sensitivity analysis. The findings reveal that country rankings are largely consistent and that food security performance is shaped not by a single indicator, but by a combination of interrelated structural factors. In particular, for countries in the lower performance group, food insecurity does not stem from a single deficiency but rather from the combined effects of vulnerabilities related to economic access, supply and price stability, and production structures. This finding suggests that the focus of policy discussions should not merely be on countries' positions in the rankings, but rather on how the structural weaknesses determining these positions can be mitigated. In this context, strengthening economic accessibility emerges as the foremost policy priority for lower-ranked countries. The high cost of a healthy diet and the relatively large share of the population unable to afford healthy food indicate that food insecurity is directly linked not only to production levels, but also to income distribution and purchasing power. Accordingly, the targeted design of food assistance mechanisms, the implementation of subsidies to improve access to nutritious food for low-income groups, and the integration of social policy instruments within a food security framework are of critical importance. The second key policy area concerns the stabilization of food supply and prices. Food supply variability and price anomalies emerge as direct weakening factors of food security, particularly in lower-performing countries. This situation indicates that agricultural production systems and supply chains are insufficiently resilient to climate-related, economic, and trade-induced shocks. Strengthening stock management mechanisms for strategic commodities, developing market-balancing intervention tools, and implementing regulatory policies aimed at reducing price volatility should therefore be prioritized. Third, reducing external dependency represents a fundamental structural requirement for lower-performing countries. Net import dependency in agriculture and livestock sectors increases vulnerability to food insecurity, especially during periods of global crisis. In this regard, restructuring support schemes to enhance domestic production capacity, promoting production models that reduce input dependency, and prioritizing policies aimed at increasing agricultural value added are essential. The primary objective is not to achieve full self-sufficiency in the short term, but rather to establish a production structure that enhances resilience to external shocks for critical products. Finally, the results highlight the guiding role of public policies as a determining factor, particularly in lower-ranked countries. While the share of agriculture in government expenditure alone does not guarantee high performance, how and where these expenditures are allocated is of critical importance for food security. Investments in infrastructure, storage, logistics, and the support of small-scale producers stand out as policy instruments that can indirectly yet sustainably strengthen food security.

For future research, incorporating qualitative dimensions such as governance quality, institutional capacity, and food system resilience into the evaluation framework may contribute to deepening the analysis. Moreover, introducing a temporal dimension through dynamic analyses and monitoring the long-term impacts of policy interventions would enable more comprehensive assessments of food security performance. Overall, this study demonstrates that findings derived from MCDM approaches provide policymakers not only with an answer to the question “Which country ranks where?”, but more importantly with analytical and holistic insights into “Why does it rank there, and how can its performance be improved?”

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GEÇİCİ KAPAK

Kapak tasarımı devam ediyor.