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A Robust Data-Driven Framework for Evaluating National Industry 4.0 Performance: A Hybrid Learning and Decision-Making Approach

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Abstract: This study aims to suppress This study proposes a robust, data-driven framework to evaluate national Industry 4.0 performance by integrating unsupervised clustering, neural network–based importance estimation, permutation feature importance, and multi-criteria decision-making. Unlike conventional approaches relying on predefined or equal weights, the proposed framework derives criterion weights directly from data while accounting for structural uncertainty across alternative clustering schemes. The resulting robust weights are incorporated into TOPSIS to generate consistent country rankings. An empirical application using the Network Readiness Index, Global Innovation Index, and National Cyber Security Index demonstrates the effectiveness of the framework. The results identify human capital, governance capacity, and cybersecurity preparedness as the most influential dimensions of Industry 4.0 performance. Sensitivity analysis and equal-weight comparisons further confirm the stability of the rankings, providing a transparent and reliable framework for supporting national digital transformation strategies.

Keywords: Industry 4.0, multilayer perceptron (MLP), multi-criteria decision-making, data-driven weighting, robustness analysis.

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1. Introduction and Related Studies

The Industry 4.0 concept was first introduced at the Hannover Fair in 2011 and refers to a digital and smart manufacturing paradigm centered on customer-oriented production, real-time communication among people, machines, and products, and a high degree of operational flexibility (Xu et al., 2021; Doğruel Anuşlu & Fırat, 2019a). This paradigm represents a fundamental transformation in industrial systems.

Industry 4.0 encompasses a wide range of advanced technologies, including smart robots, smart factories, cyber-physical systems, the Internet of Things (IoT), big data analytics, artificial intelligence, cybersecurity, cloud computing, augmented reality (AR), blockchain technologies, and sensor-based systems (Özköse & Güney, 2023; Bai et al., 2020; Doğruel Anuşlu & Fırat, 2019a). Through the integration of these technologies, cyber-physical systems are able to communicate and collaborate with each other and with humans in real time via IoT infrastructures. This interaction is further supported by external organizational services accessible to both internal and external stakeholders across the production chain. As a result, manufacturing systems achieve higher levels of innovation, benefit from significant positive externalities, and enable production activities that were previously unattainable.

Empirical studies investigating the impact of Industry 4.0 technologies on industrial production reveal that the outcomes of implementation can be grouped into several key dimensions (Trachuk & Linder, 2020). These include: (1) financial outcomes, such as increased revenues and reduced operational costs; (2) value-based transformations, including product individualization, increased privatization of goods and services, and reduced batch sizes; (3) operational improvements, such as enhanced flexibility and adaptability, accelerated production cycles, and increased efficiency; and (4) innovative and technological advancements, including shorter prototype development times, faster market introduction of new products, and higher overall technological capability. In addition to these economic and operational benefits, Industry 4.0 technologies also contribute to environmental sustainability by improving production efficiency and reducing resource consumption (Javaid et al., 2022).

Recent global statistics further highlight the growing importance of Industry 4.0 technologies. According to the International Federation of Robotics (IFR, 2023), annual installations of industrial robots reached 553,000 units in 2022, representing a 5% increase compared to the previous year. In parallel, the global smart factory market is projected to grow from USD 100.6 billion in 2024 to USD 164.0 billion by 2029 (Research and Markets, 2024), while the Internet of Things (IoT) market is expected to reach USD 2,455.66 billion by 2029 (Fortune Business Insights, 2022). These trends clearly indicate the accelerating global adoption of Industry 4.0 technologies.

The growing academic interest in Industry 4.0 is also evident in scientific publications. An examination of the Web of Science database reveals approximately 47,300 publications related to Industry 4.0. Figure 1 illustrates the keywords most frequently associated with these studies, highlighting the close relationship between Industry 4.0 and concepts such as IoT, sustainability, digitalization, and big data.

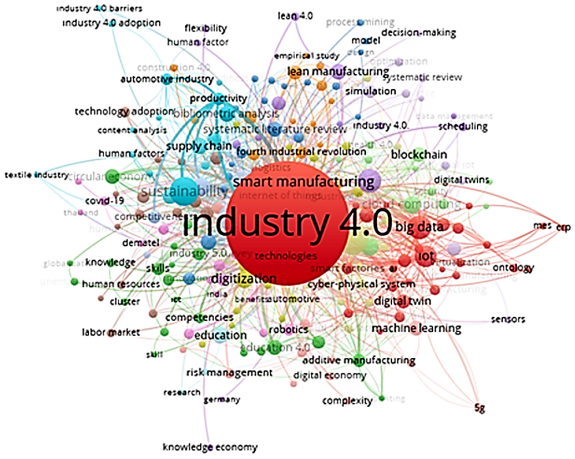


Figure 1. Industry 4.0 and related keywords (authors' own visualization created using VOSviewer).

Industry 4.0 is frequently linked with sustainability and long-term development goals. Its impacts can be observed both at the micro level, affecting individual firms and production systems, and at the macro level, shaping national strategies and public policies (Prashar, 2024; Samadhiya et al., 2024; Yang et al., 2023). From a macroeconomic perspective, countries' adaptation to Industry 4.0 is closely monitored, as

performance assessments play a crucial role in guiding national investments and policy decisions.

In this context, the evaluation and comparison of countries' Industry 4.0 performance require comprehensive and reliable indicators. This study focuses on constructing a country-level Industry 4.0 performance ranking by jointly utilizing multiple internationally recognized indices. Specifically, the Network Readiness Index (NRI), which focuses on information and communication technologies, the Global Innovation Index (GII), which captures innovation-related indicators closely linked to ICT, and the National Cyber Security Index (NCSI), which addresses information security as a core component of Industry 4.0 (Doğruel Anuşlu & Fırat, 2019a), are jointly considered to provide a holistic assessment.

Several studies have employed these indices individually or in combination using various analytical techniques. Silva et al. (2022) analyzed NRI data from 2013 to 2016 using LASSO analysis to identify indicators with the strongest economic and social impacts. Huarng and Yu (2022), based on 2020 NCSI data, proposed an alternative country ranking by examining positively and negatively correlated GII indicators through fuzzy set qualitative comparative analysis. Doğruel and Fırat (2021) applied Classification and Regression Tree (CART) and linear regression analysis to estimate GII values using NRI indicators and to identify the most discriminative factors.

In addition to statistical and regression-based approaches, recent research has increasingly incorporated advanced soft computing and fuzzy-based multi-criteria decision-making frameworks to evaluate Industry 4.0 adoption and strategic positioning. For instance, Abu-Lail et al. (2025) proposed a Circular-Fermatean fuzzy decision-making model to assess Industry 4.0 adoption strategies in small and medium enterprises, emphasizing the role of uncertainty-aware and hybrid evaluation structures. Such studies demonstrate the growing tendency to integrate robust decision-support mechanisms within Industry 4.0 performance assessment contexts.

In related research, Doğruel Anuşlu and Fırat (2020) developed regression-based models to analyze the effects of innovation on sustainable development and environmental performance using GII, the Sustainable Development Goals Index, and the Environmental Performance Index. Furthermore, Doğruel Anuşlu and Fırat (2019b) employed cluster analysis to group countries within the scope of Industry 4.0 using GII, the SDGs Index, the Logistics Performance Index, and the Environmental Performance Index.

Multidimensional country-level performance assessments frequently rely on composite indicator construction, where indicator selection, weighting schemes, and aggregation assumptions play a decisive role in shaping ranking outcomes. The construction of composite indicators has long been associated with concerns regarding the arbitrariness of weighting and aggregation schemes, particularly with respect to benchmark selection and compensability assumptions (Fusco, 2023). Recent research has also emphasized the importance of incorporating robustness considerations into evaluation frameworks to enhance the reliability of policy interpretations (Vidoli et al., 2024).

In response to these challenges, hybrid soft computing approaches that integrate clustering with complementary learning and decision mechanisms have been increasingly adopted to improve analytical robustness and interpretability in complex decision environments. For example, Khalili-Damghani et al. (2018) proposed a hybrid framework combining clustering, rule mining, and decision tree analysis to enhance segmentation performance in real-world applications. Such hybridization strategies demonstrate the effectiveness of integrating multiple analytical components within a unified structure, particularly in multidimensional evaluation and ranking problems.

Despite these advances, existing approaches still rely on fixed structural assumptions and do not explicitly account for uncertainty arising from alternative classification schemes. In particular, the stability of learned importance structures under label uncertainty remains insufficiently explored in country-level Industry 4.0 assessment.

In multidimensional learning problems, assuming equal contribution across input variables may obscure latent structural patterns and weaken the identification of truly discriminative factors. Recent research shows that differentiating feature contributions based on their information content can significantly enhance analytical performance by reducing the influence of weakly informative or irrelevant dimensions (Jiang et al., 2025). However, beyond

the issue of learning data-driven weights, relatively limited attention has been paid to the robustness and stability of the derived importance structures themselves. In particular, weight profiles obtained from a single modeling configuration may be sensitive to modeling assumptions and can lead to unstable ranking outcomes when directly embedded into downstream evaluation or decision-making procedures.

Consequently, there remains a clear need for comprehensive frameworks that integrate multiple international indices, derive criterion weights in a fully data-driven manner, and explicitly address the robustness of the resulting weighting and ranking structures in country-level performance assessment.

Recent studies have highlighted the effectiveness of hybrid frameworks that integrate deep learning with decision-support mechanisms for complex evaluation problems (Lozano et al., 2026).

Against this background, this study proposes a robust and data-driven evaluation framework designed to address structural uncertainty and improve the reliability of country-level Industry 4.0 performance assessment.

Data-driven importance estimates derived from learning-based models can be effectively translated into consistent and interpretable ranking outcomes. The evaluation of country-level Industry 4.0 performance provides an empirical setting to demonstrate the applicability of the proposed framework to complex and multidimensional assessment problems.

Despite the growing body of research on Industry 4.0 performance evaluation, existing studies often rely on predefined weighting schemes or single-model configurations, which may lead to biased or unstable ranking outcomes. In particular, limited attention has been paid to the robustness of learned importance structures under alternative data-driven assumptions. This limitation reduces the reliability of country-level comparisons and weakens the practical applicability of such evaluation frameworks in policy-making contexts.

This study makes three main contributions to the literature on Industry 4.0 performance evaluation. First, a hybrid learning-based framework is developed by integrating unsupervised clustering, neural network–based importance estimation, and multi-criteria decision-making into a unified structure. This integrated design enables the systematic propagation of data-driven insights into ranking outcomes. Second, a fully data-driven criterion weighting mechanism is introduced based on permutation feature importance. Unlike conventional approaches that rely on equal or subjective weights, the proposed method derives criterion importance directly from data, enhancing objectivity and interpretability. Third, a robustness-oriented aggregation strategy is proposed to account for structural uncertainty arising from alternative clustering schemes. By combining multiple importance profiles, the framework produces stable and reproducible ranking results, as confirmed through extensive sensitivity analysis.

The remainder of this paper is structured as follows. Section 2 introduces the international indices and data structure. Section 3 presents the proposed methodology, including the integration of clustering, neural network–based importance estimation, and multi-criteria evaluation. Section 4 reports and discusses the empirical results. Finally, Section 5 concludes the study with key findings and policy implications.

2. International Indices

To achieve a comprehensive ranking of countries' Industry 4.0 performance, three internationally recognized indices that are widely used in academic studies are included in the scope of this research: the Network Readiness Index (NRI), the Global Innovation Index (GII), and the National Cyber Security Index (NCSI). Each index captures a distinct yet complementary dimension of Industry 4.0, enabling a multidimensional evaluation of national performance.

2.1 The Network Readiness Index (NRI)

The Network Readiness Index evaluates countries' preparedness to participate in and benefit from the network economy. The 2022 report of the index covers 131 countries and is structured around four main pillars: Technology, People, Governance, and Impact (Portulans Institute, Saïd Business School and University of Oxford, 2022). Technology is considered the core of the network economy, reflecting the extent to which a country possesses and can effectively utilize digital technologies to remain competitive in the global economy.

The index assesses technological readiness by examining access to technology, available resources, and the ability of individuals and organizations to use these technologies efficiently. In addition, governance-related aspects such as regulatory frameworks, digital inclusion, and network security are evaluated to reflect the safety and sustainability of digital transformation. Overall, network readiness serves as an important instrument for enhancing economic growth and social prosperity. However, the diffusion of innovation often widens the socioeconomic gap between early and late adopters within a system (Değerli et al., 2015). According to the NRI 2022 report, the United States, Singapore, Sweden, the Netherlands, and Switzerland rank among the most successful countries, with Europe emerging as the most successful continent, hosting three of the top five countries.

2.2 The Global Innovation Index (GII)

The Global Innovation Index measures and ranks the innovation performance of countries based on a broad set of variables influencing innovation processes (Gürtuna & Polat, 2020). In the 2022 report, the index covers 132 countries and is composed of two main components: the Innovation Input Sub-Index and the Innovation Output Sub-Index (World Intellectual Property Organization, 2022). While the Innovation Input Sub-Index reflects factors that enable innovative activities, the Innovation Output Sub-Index captures the tangible results of these activities.

Over time, the GII has been widely used not only to assess national innovation capacities but also to evaluate the global impact of innovation performance (Doğruel and Fırat, 2021). The data utilized in the index are obtained from reliable sources such as central banks, national statistical agencies, and other official government institutions, ensuring the comparability and consistency of the reported indicators across countries.

2.3 National Cyber Security Index (NCSI)

The National Cyber Security Index evaluates countries' preparedness to prevent cyber threats and effectively respond to cyber incidents. First introduced in 2014, the NCSI also functions as a repository of publicly available materials and tools that demonstrate a country's capacity to establish and maintain a national cybersecurity system (Kravets, 2019). Unlike many composite indices, NCSI data are dynamic; new evidence is continuously assessed, and when validated, rankings are updated accordingly.

The index currently covers 175 countries, with the most recent data update conducted in July 2022 (e-Governance Academy, 2023). NCSI focuses on concrete governmental actions and practices in the field of cybersecurity, including existing legislation, institutional structures, cooperation mechanisms, and achieved outcomes. The index is developed and maintained by the e-Governance Academy, a center of excellence established in 2002 by the Estonian Government, the Open Society Institute, and the United Nations Development Programme (e-Governance Academy, 2023). The Academy plays a significant role in supporting national cybersecurity policy design and implementation processes.

3. The Proposed Methodology

The proposed methodology consists of two main components: (i) a learning layer for data-driven criterion importance estimation and (ii) a decision layer for country ranking. The overall workflow includes data preprocessing, clustering-based label generation, MLP-based importance learning, robust weight aggregation, and TOPSIS-based ranking. This structure enables a systematic and interpretable evaluation of Industry 4.0 performance.

This study proposes a hybrid data-driven framework that integrates machine learning–based importance learning with a downstream decision-making layer for robust country-level performance evaluation. The overall workflow of the proposed methodology is illustrated in Figure 2, which outlines the sequential structure of the framework from data preparation to final ranking outcomes.

As shown in Figure 2, the methodology is organized into two interconnected components. In the first component, machine learning models are employed to learn criterion importance in a fully data-driven manner, with an explicit focus on the reliability and stability of the derived weighting structure rather than on predictive accuracy alone. In the second component, the learned importance profiles are embedded into a multi-criteria decision-making mechanism to generate interpretable and comparable ranking results.

By explicitly separating the learning layer from the decision layer, the proposed framework enables a systematic examination of how machine-learning-derived importance estimates propagate into evaluation and ranking outcomes. Robustness is addressed through the integration of multiple importance configurations and through subsequent sensitivity analysis, ensuring that the final results are not driven by a single modeling realization but instead reflect stable system behavior under reasonable perturbations.

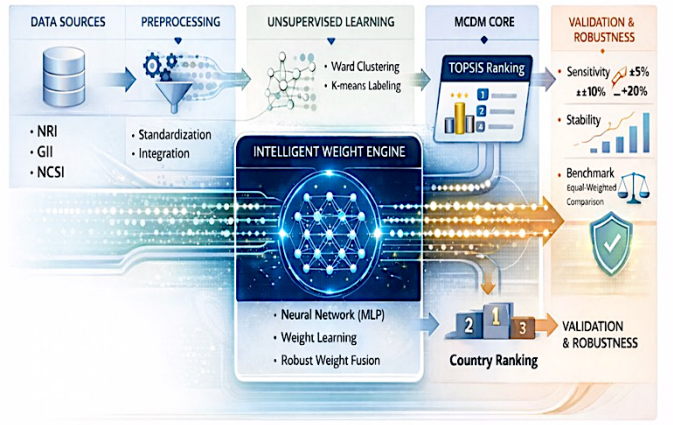


Figure 2. Proposed methodology (developed by the authors).

The first stage involves data collection and preprocessing. The dataset is constructed using indicators obtained from internationally recognized indices related to the core components of Industry 4.0, namely the Network Readiness Index (NRI), the Global Innovation Index (GII), and the National Cyber Security Index (NCSI). After merging the indices based on common countries, the resulting dataset is standardized to eliminate scale-related biases. The final dataset consists of multiple Industry 4.0–related indicators for 120 countries and does not include a predefined target variable.

In the absence of labeled data, unsupervised clustering techniques are employed to generate country performance classes. To explicitly account for clustering-induced label uncertainty, two fundamentally different clustering approaches are applied: Ward's hierarchical clustering and K-means clustering. Each method produces an independent three-category class structure representing different levels of Industry 4.0 performance. The agreement between these clustering results is later assessed to evaluate the robustness of the generated labels.

In the next stage, the generated class labels are used to train multilayer perceptron (MLP) classification models. Separate MLP models are trained for each clustering-based labeling scheme using a train–test split and hyperparameter optimization. Instead of relying on internal network weights, criterion importance is derived using permutation-based feature importance. This approach measures the decrease in model performance caused by randomly permuting each input variable, thereby providing an interpretable and decision-oriented estimate of criterion weights.

To reduce sensitivity to clustering structure and enhance robustness, the criterion weight vectors obtained from different clustering configurations are aggregated into a single robust weight vector. This aggregated weight structure reflects the combined importance of Industry 4.0 indicators across alternative labeling schemes and mitigates the impact of clustering-related variability.

Finally, the robust criterion weights are incorporated into the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank countries according to their Industry 4.0 performance. To further validate the reliability of the proposed methodology, extensive sensitivity analysis is conducted by perturbing the criterion weights under multiple scenarios and examining the stability of the resulting rankings. This ensures that the final country rankings are not only data-driven but also robust to reasonable variations in model assumptions.

3.1 Clustering-Based Label Generation

In the proposed framework, unsupervised learning is employed to reveal latent structural patterns among countries based on Industry 4.0–related indicators. Since the dataset does not contain a predefined target variable, clustering techniques are used to generate performance-based class labels.

Rather than treating clusters as definitive performance categories, they are interpreted as structural representations that support subsequent learning stages. In this way, clustering provides an initial organization of the data and facilitates more informative importance learning in the downstream machine learning layer.

Cluster analysis is employed to group countries with high intra-cluster similarity and high inter-cluster dissimilarity based on Industry 4.0–related indicators (Sinaga & Yang, 2020; Doğruel Anuşlu and Fırat, 2019b).

To explicitly account for clustering-induced label uncertainty, two fundamentally different clustering techniques are applied. First, Ward's hierarchical clustering method, an agglomerative approach, is used to iteratively merge observations by minimizing within-cluster variance. Second, the K-means algorithm partitions the dataset into a predefined number of clusters by minimizing the sum of squared errors between data points and their respective cluster centroids (Yu et al., 2018; Ikotun et al., 2023).

The K-means clustering objective function is expressed as follows:

$$SSE = \sum_{k=1}^{K} \quad \sum_{x_i \in c_k} \quad \left|\left|x_i - m_k\right|\right|^2 \qquad (1)$$

where x_i denotes the i-th observation, C_k is cluster k, m_k is the centroid of cluster k, and K is the number of clusters.

Each clustering method produces an independent three-class structure representing alternative performance categorizations of countries. Rather than selecting a single class configuration, the Ward-based and K-means–based results are treated as parallel labeling schemes and are used in the downstream learning stage to evaluate the robustness of importance estimation and ranking outcomes. This approach enables the framework to account for structural uncertainty and improves the reliability of the final assessment.

3.2 MLP-Based Modeling and Permutation-Based Weight Extraction

Artificial neural networks (ANNs) are widely used in machine learning due to their strong capability to model complex and nonlinear relationships among variables (Abiodun et al., 2018; Ayyıldız et al., 2022; Yazıcı & Taşkın, 2023). Recent studies have further demonstrated the effectiveness of machine learning models in enhancing predictive performance in engineering systems (Sathiparan & Jeyananthan, 2025). Among various ANN architectures, the multilayer perceptron (MLP) is one of the most commonly adopted feedforward neural networks for classification tasks, consisting of an input layer, one or more hidden layers, and an output layer with nonlinear activation functions (Samadianfard et al., 2022; Sabry, 2023).

In particular, MLP architectures have been successfully integrated with various machine learning techniques to construct hybrid learning frameworks that enhance analytical performance and decision support capability. For instance, Lai et al. (2021) demonstrated that neural network–based structures can effectively extract informative patterns from high-dimensional data.

In this study, MLP models are employed not as end-to-end predictive tools, but as an intermediate learning mechanism for deriving data-driven criterion importance. The classification task is therefore utilized to uncover meaningful relationships between Industry 4.0 indicators and clustering-based class structures, rather than being treated as the primary objective of the framework.

Accordingly, MLP models are trained using the class labels generated through clustering. Separate models are constructed for each clustering configuration to avoid dependence on a single labeling structure and to capture alternative data representations. Model training is performed using a train–test split, and network parameters are optimized through backpropagation and gradient-based learning in order to minimize classification error (Yan, 2023).

A general MLP neuron can be expressed as (Altay & Varol Altay, 2023; Damrongsakmethee & Neagoe, 2019):

$$y_j = \varphi\left(\sum_{i=1}^{n} \quad \left(w_{ij}.x_i + b_j\right)\right) \qquad (2)$$

where x_i represents the input features, w_{ij} denotes the connection weights, b_j is the bias term, ϕ is a nonlinear activation function, and y_j is the output.

Importantly, the trained MLP models are not interpreted through internal network parameters. Instead, criterion importance is derived using permutation-based feature importance, which evaluates the contribution of each input variable by measuring the decrease in model performance when the values of that variable are randomly permuted. Variables that lead to larger performance degradation are considered more important in determining the underlying structure.

Compared to direct inspection of network weights, permutation-based importance provides a more robust, interpretable, and model-independent estimation of criterion weights. Furthermore, it reduces sensitivity to network architecture and scaling effects, making it particularly suitable for decision-support applications.

The importance vectors obtained from different clustering-based MLP models are subsequently used to construct a robust weighting structure, which serves as the basis for the downstream multi-criteria decision-making analysis.

3.3 Robust Weight Integration and TOPSIS-Based Ranking

To reduce sensitivity to clustering structure and enhance the robustness of the evaluation process, the criterion weight vectors obtained from different clustering-based MLP models are aggregated into a single robust weight vector. This aggregation ensures that the final weight structure reflects consensus importance patterns across alternative labeling schemes rather than being driven by a single model configuration.

Using these robust criterion weights, countries are ranked according to their Industry 4.0 performance through the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a widely used multi-criteria decision-making method (Chakraborty, 2022; Ciardiello & Genovese, 2023; Shih & Olson, 2022). In the proposed framework, TOPSIS serves as the final decision layer that translates machine learning–derived importance weights into interpretable and comparable country-level ranking outcomes.

In the first step, a decision matrix is constructed, where rows represent countries (alternatives) and columns represent Industry 4.0 indicators (criteria). The decision matrix is then normalized using vector normalization as follows:

$$Zij = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{n} \ (y_{ij})^2}} (i = 1, \dots, n; \ j = 1, \dots, k) \qquad (3)$$

where y_{ij} denotes the original value of criterion j for country i, z_{ij} represents the normalized value of criterion j for country i, $i = 1, \dots, n$ indexes the countries, $j = 1, \dots, k$ indexes the criteria, n is the number of countries, and k is the number of criteria.

In the second step, the normalized decision matrix is weighted using the robust criterion weights obtained from the previous stage. Let w_j denote the robust weight of criterion j, satisfying $\sum_{j=1}^{k} \ w_j = 1$. Accordingly, the weighted normalized decision matrix is calculated as:

$$v_{ij} = w_j z_{ij} \qquad (4)$$

where z_{ij} represents the normalized value of criterion j for country i obtained in the previous step, and v_{ij} denotes the weighted normalized value of criterion j for country i.

Next, the positive ideal solution A+ and the negative ideal solution A− are determined by selecting the maximum and minimum values of each column in the weighted normalized matrix:

$$A^+ = \{j = 1, \dots, k\},$$
$$A^- = \{j = 1, \dots, k\} \qquad (5)$$

where A^+ and A^-denote the positive ideal solution and the negative ideal solution, respectively, obtained by selecting the maximum and minimum values of each criterion from the weighted normalized decision matrix $[v_{ij}]$.

After determining the positive and negative ideal solutions, the separation measures of each country from the ideal solutions are computed using the Euclidean distance. The separation measures from the positive and negative ideal solutions are then computed using Euclidean distance:

$$S_i^+ = \sqrt{\sum_{j=1}^{k} \ \left(v_{ij} - A_j^+\right)^2} (i = 1, \dots \dots \dots, n) \qquad (6)$$

$$S_i^- = \sqrt{\sum_{j=1}^{k} \ \left(v_{ij} \ - A_j^-\right)^2} (i = 1, \dots \dots \dots, n) \qquad (7)$$

where S_i^+ and S_i^- denote the Euclidean distances of country i from the positive ideal solution A^+ and the negative ideal solution A^-, respectively, v_{ij} represents the weighted normalized value of criterion j for country i, and v_j^+ and v_j^- denote the ideal values of criterion j in A^+ and A^-.

Finally, the relative closeness coefficient of each country to the ideal solution is calculated as:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \ 0 \le C_i \le 1 \qquad (8)$$

where C_i denotes the relative closeness coefficient of country i to the ideal solution, with larger values of C_i indicating better overall Industry 4.0 performance.

Countries are ranked in descending order of C_i, where higher values indicate better Industry 4.0 performance.

To further assess the reliability of the obtained rankings, sensitivity analysis is conducted by perturbing the robust criterion weights under multiple scenarios. Examining the stability of ranking outcomes under these perturbations provides additional validation of the robustness and consistency of the proposed hybrid learning and decision-support framework.

4. The Numerical Application

In order to empirically demonstrate the proposed robust hybrid framework, the methodology illustrated in Figure 2 is applied to evaluate countries' Industry 4.0 performance. All stages of the analysis—including data collection, preprocessing, clustering, neural network modeling, permutation-based feature importance, robust weight aggregation, and TOPSIS-based ranking—are implemented in the Python programming language to ensure transparency, reproducibility, and end-to-end consistency of the computational workflow.

This study utilizes data obtained from the 2024 editions of the Network Readiness Index (NRI), the Global Innovation Index (GII), and the National Cyber Security Index (NCSI). After matching countries that appear simultaneously in all three indices, a final dataset comprising 120 countries and seven Industry 4.0–related indicators is constructed. The indicators used in the analysis are presented in Table 1. To eliminate scale effects and ensure comparability among indicators, all variables are standardized prior to analysis.

Table 1. Features used in the dataset.

Indexes	Features
NRI	Technology
GII	Input
NCSI	Overall

Since the dataset does not contain a predefined target variable, unsupervised learning techniques are first employed to generate country performance classes. Both Ward's hierarchical clustering and K-means clustering are applied to the standardized dataset. The optimal number of clusters is determined using a combination of the elbow method and silhouette analysis, as illustrated in Figure 3. Both criteria consistently indicate that a three-cluster structure provides the most appropriate partitioning of countries according to their Industry 4.0 characteristics.

The dendrogram obtained using Ward's hierarchical clustering method is shown in Figure 4, revealing a clear three-level hierarchical structure. In parallel, K-means clustering partitions the 120 countries into three distinct clusters. These clusters are interpreted as representing relatively high, medium, and low levels of Industry 4.0 performance.

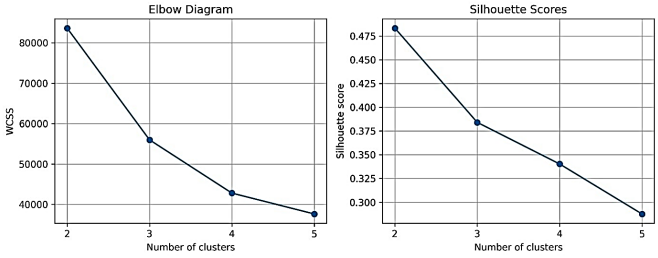


Figure 3. Elbow and silhouette score plots.

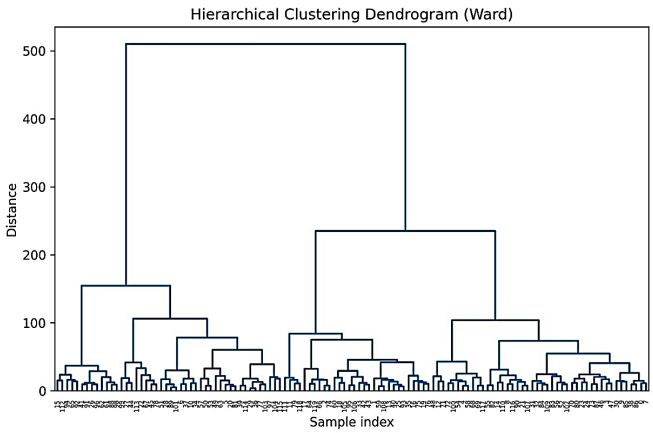


Figure 4. Dendrogram (Ward).

Importantly, the two clustering methods produce alternative but related label structures, allowing clustering-induced label uncertainty to be explicitly examined in subsequent modeling stages.

4.1 Robust MLP Modeling and Data-Driven Weight Extraction

After constructing the integrated dataset (120 countries × 7 indicators), the proposed framework proceeds by generating class labels through unsupervised clustering. Two alternative labeling schemes are considered to explicitly account for clustering-induced label uncertainty: (i) Ward's hierarchical clustering and (ii) K-means clustering. Rather than relying on a single labeling outcome, both schemes are carried forward to the supervised learning stage to ensure that subsequent inferences are not driven by a particular clustering mechanism.

4.1.1 Leakage-Free Cross-Validation and Hyperparameter Optimization

To avoid any form of data leakage, all preprocessing and model selection steps are performed strictly within the training folds of the cross-validation procedure. In particular, feature scaling and MLP training are executed through a pipeline, ensuring that the scaler is fit only on the training portion of each fold and never on the held-out data. Model selection is performed via cross-validation using the weighted F1-score, which is appropriate for potential class imbalance across the three cluster-derived classes.

For the Ward-based labels, the best cross-validated weighted F1-score is 0.8873, obtained with the following hyperparameters: activation = ReLU, solver = Adam, $\alpha = 0.0001$, hidden layer sizes = (50, 50), and learning rate = constant.

For the K-means–based labels, the best cross-validated weighted F1-score improves to 0.9154, achieved with activation = logistic, solver = Adam, $\alpha = 0.0001$, hidden layer sizes = (100,), and learning rate = constant. The fact that the optimal architecture differs across labeling schemes further supports the methodological choice of retaining both Ward and K-means labels, since each clustering structure induces a distinct decision boundary in the supervised stage.

4.1.2 Generalization Performance Under Ward and K-Means Labels

After selecting the best models via cross-validation, the resulting classifiers are evaluated using a held-out test set. For the Ward-labeled learning task, the final model achieves train accuracy = 0.9285 and train F1_weighted = 0.9275. On the test set, the Ward-based model yields test accuracy = 0.8888 and test F1_weighted = 0.8835. These results indicate strong generalization with a relatively small train–test gap, suggesting that the model captures stable patterns rather than memorizing the training set.

For the K-means–labeled learning task, the final model achieves train accuracy = 0.9523 and train F1_weighted = 0.9525. On the held-out test set, it achieves test accuracy = 0.9166 and test F1_weighted = 0.9138. The test classification report shows that the model performs consistently across classes, with misclassifications primarily occurring between neighboring clusters, which is expected given that the cluster labels reflect graded performance levels rather than sharply separated categories.

Overall, both labeling schemes produce high-performing predictive models, while the K-means labeling yields slightly stronger cross-validated and test performance in this dataset. Importantly, since the objective of the supervised stage is not solely classification accuracy but reliable importance estimation, both trained models are retained for robust weight extraction.

The agreement between Ward and K-means clustering results is quantified using the Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI). The obtained ARI (≈0.66) and NMI (≈0.70) values indicate a moderate-to-high level of agreement between the two clustering schemes, suggesting that both methods capture broadly similar macro-level grouping structures in the data while still preserving meaningful methodological differences. This observation provides a quantitative rationale for incorporating both clustering outcomes into the subsequent robust weighting procedure rather than relying on a single labeling scheme.

4.2 Robust Criterion Weighting via Permutation-Based Importance

Instead of interpreting raw neural network parameters, criterion weights are extracted using permutation-based feature importance computed with the weighted F1-score objective. For each trained model, the marginal contribution of an indicator is quantified by measuring the decrease in predictive performance when that feature is randomly permuted while other features remain intact. This approach yields model-agnostic, performance-grounded importance values.

Permutation-based weights are computed separately for (i) the Ward-based best MLP and (ii) the K-means–based best MLP. The resulting normalized weights, along with the final

robust weights obtained by averaging the two schemes, are summarized in Table 2. Specifically, the robust weights (Ward and K-means average) are:

Table 2. Robust criterion weights.

Feature	Ward	K-means	Robust	K-means	Ward
People	0.3578	0.1378	0.2478	4	1
Governance	0.3173	0.1642	0.2408	2	2
NCSI	0.2457	0.2262	0.2360	1	3
GII_Input	0.0509	0.0974	0.0741	7	4
Impact	0.0179	0.1100	0.0640	5	5
Tech	0.0102	0.1624	0.0863	3	6
GII_Output	0.0000	0.1017	0.0508	6	7

Notably, the Ward-only and K-means–only weight rankings are not identical. The rank correlation between Ward-based and K-means–based weight orders are Spearman $\rho = 0.4285$ and Kendall $\tau = 0.2380$. This finding confirms that the inferred importance profile is meaningfully influenced by the labeling scheme. Therefore, adopting an aggregated (robust) weight vector is methodologically justified: it reduces dependence on a single clustering outcome and yields a more stable, reproducible set of criterion weights for the subsequent MCDM stage.

4.3 TOPSIS-Based Country Ranking

Following the extraction of data-driven criterion weights through the MLP-based analysis, the next step of the proposed framework focuses on translating these weights into an interpretable country-level performance ranking. To this end, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is employed as the final decision-making mechanism.

In contrast to conventional multi-criteria ranking studies that assume equal importance across indicators, the present study incorporates robustly aggregated MLP-derived weights into the TOPSIS procedure. These weights reflect the relative importance of each Industry 4.0 indicator as learned from the data, while simultaneously accounting for clustering-induced label uncertainty through the joint consideration of Ward- and K-means–based labeling schemes. As a result, the obtained rankings are not driven by subjective assumptions or a single clustering outcome, but instead rely on a stable, data-informed weighting structure.

Applying TOPSIS with the aggregated criterion weights yields a comprehensive Industry 4.0 performance ranking for 120 countries based on seven indicators. The resulting TOPSIS scores represent each country's relative closeness to the ideal Industry 4.0 profile, thereby enabling a direct and interpretable comparison of national performance levels.

Figure 5 visually illustrates the TOPSIS scores of a selected group of high-performing and low-performing countries, providing an intuitive overview of the performance gap between leading and lagging groups. Rather than presenting the complete ranking, the figure focuses on representative extremes in order to highlight relative differences in Industry 4.0 performance. The clear separation observed in the TOPSIS scores suggests that the proposed framework effectively distinguishes countries with substantially different performance levels.

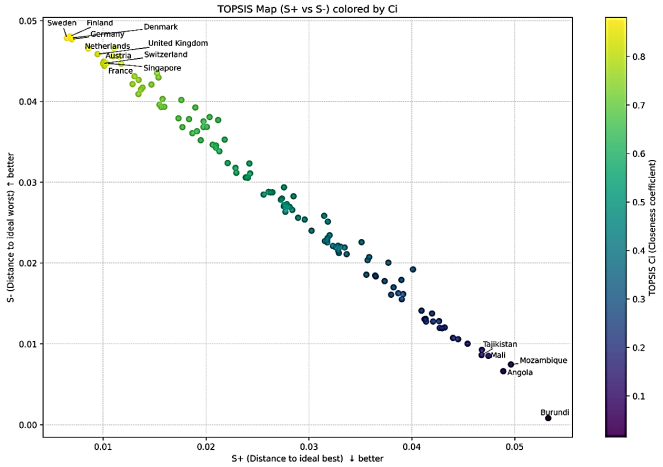


Figure 5. TOPSIS performance map of countries based on MLP-derived weights.

For completeness and transparency, the full ordered list of all 120 countries along with their TOPSIS scores and rankings is provided in Appendix A.

Overall, the TOPSIS-based ranking constructed using robust MLP-derived weights provides a holistic and objective assessment of countries' Industry 4.0 performance. While this ranking captures the relative standing of countries under the proposed weighting scheme, it remains important to examine whether the observed ordering is stable under potential variations in criterion weights. Accordingly, the robustness of the obtained rankings is evaluated through a sensitivity analysis in the following section.

4.4 Sensitivity Analysis and Ranking Robustness

While data-driven weighting schemes improve the objectivity of multi-criteria decision-making frameworks, it is equally important to examine whether the resulting rankings remain

stable under reasonable variations in criterion importance. Accordingly, a comprehensive sensitivity analysis is conducted to evaluate the robustness of the proposed MLP–TOPSIS-based Industry 4.0 country ranking.

Following a one-at-a-time adjustment strategy, the weight of each Industry 4.0 indicator is independently increased and decreased by ±5%, ±10%, and ±20%, while the remaining weights are proportionally re-scaled to preserve the overall weighting structure. For each adjustment scenario, the TOPSIS procedure is re-applied and the resulting rankings are compared with the baseline ranking derived from the robustly aggregated MLP-based weights.

Ranking stability is evaluated using complementary quantitative measures. Specifically, Spearman rank correlation coefficients are employed to assess the overall consistency between the baseline and adjusted rankings, while the overlap ratio of the top 10 ranked countries is used to evaluate the stability of the highest-performing group. The detailed numerical results of this analysis are reported in Table 3.

Table 3. Detailed sensitivity table.

criterion	change	spearman_rho	top10_overlap	max_abs_
GII_Input	10%	0.999951	1.0	0.006816
GII_Input	20%	0.999917	1.0	0.013532
GII_Input	5%	0.999986	1.0	0.003420
GII_Input	-10%	0.999958	1.0	0.006918
GII_Input	-20%	0.999958	1.0	0.013939
GII_Input	-5%	0.999986	1.0	0.003446
GII_Output	10%	0.999903	1.0	0.004802
GII_Output	20%	0.999847	1.0	0.009557
GII_Output	5%	0.999979	1.0	0.002407
GII_Output	-10%	0.999944	1.0	0.004852
GII_Output	-20%	0.999896	1.0	0.009753
GII_Output	-5%	0.999965	1.0	0.002420
Governance	10%	0.999660	1.0	0.017852
Governance	20%	0.999257	1.0	0.034883
Governance	5%	0.999854	1.0	0.009032
Governance	-10%	0.999674	1.0	0.018733
Governance	-20%	0.999055	1.0	0.038413
Governance	-5%	0.999896	1.0	0.009252
Impact	10%	0.999986	1.0	0.005953
Impact	20%	0.999979	1.0	0.011831
Impact	5%	0.999993	1.0	0.002986
Impact	-10%	0.999972	1.0	0.006030
Impact	-20%	0.999958	1.0	0.012138
Impact	-5%	0.999979	1.0	0.003005
NCSI	10%	0.998903	0.9	0.017615
NCSI	20%	0.997069	0.8	0.034437
NCSI	5%	0.999611	0.9	0.008910
NCSI	-10%	0.999187	0.9	0.018467
NCSI	-20%	0.997493	0.8	0.037849
NCSI	-5%	0.999674	1.0	0.009123
People	10%	0.999604	0.9	0.018190
People	20%	0.998833	0.9	0.035522
People	5%	0.999792	1.0	0.009207
People	-10%	0.999437	0.9	0.019115
People	-20%	0.998271	0.9	0.039227
People	-5%	0.999771	0.9	0.009438
Tech	10%	0.999931	1.0	0.007819
Tech	20%	0.999854	1.0	0.015506
Tech	5%	0.999958	1.0	0.003927
Tech	-10%	0.999937	1.0	0.007956
Tech	-20%	0.999875	0.9	0.016051
Tech	-5%	0.999965	1.0	0.003961

As shown in Table 3, the proposed ranking exhibits a remarkably high degree of stability across all criteria and adjustment levels. The minimum Spearman rank correlation coefficients range between 0.997 and 0.999, while the corresponding average values consistently exceed 0.998, indicating near-perfect agreement with the baseline ranking even under substantial weight adjustments. Similarly, the minimum top-10 overlap ratios vary between 0.8 and 1.0, with average overlap values remaining above 0.88 across all indicators. These findings suggest that the composition of the leading group of countries is largely preserved, and that only minor local changes occur in response to weight variations.

A criterion-level comparison reveals that indicators such as Governance, Impact, and the GII components exhibit almost complete stability, whereas relatively higher sensitivity is observed for NCSI and People. Nevertheless, even for these indicators, the observed variations remain limited and do not propagate into broader disruptions of the overall ranking structure. This behavior indicates that the learned weighting scheme captures balanced and meaningful relationships among the indicators rather than relying on a single dominant criterion.

Taken together, the sensitivity analysis confirms that the proposed MLP–TOPSIS framework yields a robust and reliable assessment of countries' Industry 4.0 performance. The data-driven weights obtained through the neural network are situated within a stable region of the solution space, where moderate to substantial variations do not lead to disproportionate changes in ranking outcomes. This robustness enhances the credibility and practical relevance of the proposed approach for comparative country-level evaluations.

Beyond the numerical stability metrics, heatmap visualizations are employed to provide an intuitive assessment of ranking robustness across different weight adjustment scenarios. The heatmaps illustrate the relative changes in country rankings resulting from criterion-specific weight adjustments, enabling a visual inspection of both global and local sensitivity patterns. As shown in Figure 6, ranking variations are largely limited to a small number of mid-ranked countries, while top- and bottom-ranked countries exhibit highly consistent positions across all scenarios.

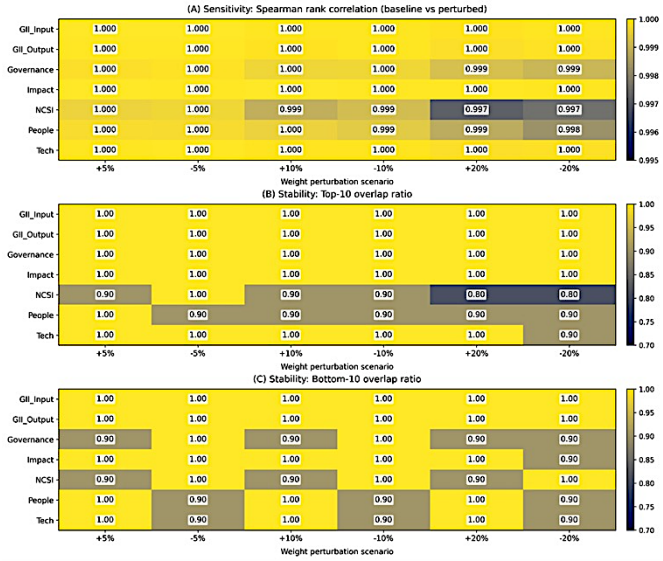


Figure 6. Heatmap visualization of ranking robustness under systematic criterion weight adjustments.

In addition to weight perturbation analysis, a baseline comparison based on an equal-weight TOPSIS configuration was conducted to explicitly examine the added value of the proposed data-driven weighting scheme. Under this scenario, all seven Industry 4.0 indicators were assigned identical importance, and the TOPSIS procedure was re-applied to generate an alternative country ranking. A detailed country-level comparison between the equal-weight and robust-weight rankings is reported in Appendix B.

The results indicate that, while the overall macro-structure of the ranking remains broadly preserved, the equal-weight configuration leads to noticeable positional changes for a substantial number of countries, particularly within the middle and lower segments of the ranking. In contrast, the proposed robust weighting scheme yields a more coherent and stable ordering, reducing arbitrary rank fluctuations caused by uniform weighting assumptions. These findings provide empirical evidence that the MLP-derived robust weights do not merely replicate a generic equal-weight structure, but instead introduce meaningful refinements that enhance discriminative power while preserving overall ranking stability.

This observation suggests that the learned MLP-based weights do not merely reproduce a generic equal-weight configuration, but instead introduce meaningful refinements that affect relative country positions. At the same time, the absence of dramatic disruptions confirms that the proposed framework avoids excessive sensitivity. Taken together, the equal-weight comparison and the sensitivity analysis demonstrate that the MLP-derived weights provide a balanced improvement over uniform weighting, enhancing discriminative power without compromising ranking stability.

5. Conclusion

This study proposes a robust hybrid framework for evaluating and ranking countries' Industry 4.0 performance by integrating unsupervised clustering, neural network–based importance learning, and multi-criteria decision-making. By combining clustering-based label generation, MLP-based importance estimation, and TOPSIS-based ranking within a unified structure, the proposed approach enables a systematic propagation of data-driven insights into interpretable and comparable decision outcomes. Unlike conventional approaches that rely on equal or expert-assigned weights, the framework derives criterion importance directly from data while explicitly accounting for uncertainty arising from alternative clustering configurations.

The empirical findings reveal that People, Governance, and National Cyber Security Index (NCSI) constitute the most influential dimensions of Industry 4.0 performance. This result indicates that Industry 4.0 readiness is primarily shaped by enabling structural foundations—namely human capital preparedness (Vong et al., 2025; Maungmee & Bhumpenpein, 2025), institutional and regulatory capacity (Crăciun et al., 2023; Jordanoski, 2025), and cybersecurity resilience (Jordanoski, 2025; Chaudhuri et al., 2025)—rather than by technological or innovation indicators in isolation. These findings are consistent with prior research emphasizing that the successful adoption of advanced digital technologies depends critically on workforce capabilities, governance effectiveness, and secure digital infrastructures.

From a policy perspective, the results suggest that national Industry 4.0 strategies should adopt an integrated and

coordinated approach that simultaneously prioritizes human capital development, governance quality, and cybersecurity preparedness. Countries achieving higher performance levels tend to exhibit balanced capabilities across these core dimensions, whereas fragmented or uneven progress across individual indicators appears insufficient for sustained and competitive digital transformation.

The robustness of the proposed framework is confirmed through extensive sensitivity analysis. The consistently high rank correlations and stable top-country compositions across multiple perturbation scenarios indicate that the resulting rankings are not driven by specific parameter choices, but instead reflect persistent structural patterns in the underlying data (Więckowski & Sałabun, 2023). This robustness enhances the reliability, interpretability, and policy relevance of the proposed framework for comparative country-level assessments.

Despite its contributions, this study has several limitations. The analysis is based on cross-sectional data and does not explicitly capture temporal dynamics of Industry 4.0 transformation. In addition, the results depend on the selected indicator set and the common-country intersection, which may lead to different outcomes under alternative configurations. Furthermore, while the proposed framework addresses robustness across clustering structures, future research may explore alternative learning-based weighting mechanisms to further enhance generalizability.

Future studies may extend the proposed framework by incorporating longitudinal data, advanced learning architectures, and dynamic policy evaluation settings. Such extensions would provide deeper insights into the evolution of Industry 4.0 performance and support more adaptive and forward-looking decision-making processes.

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Conflict of Interest

The authors declare that they have no conflicts of interest to disclose.

Data Availability

The data used in this study are publicly available from the Network Readiness Index (NRI), the Global Innovation Index (GII), and the National Cyber Security Index (NCSI). The processed dataset and the code developed for the analysis are publicly available at Zenodo:
https://doi.org/10.5281/zenodo.18712903

Ethics Approval

This study does not involve human participants or animals and does not require ethical approval.

Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this work, the authors used generative AI tools for language editing. The authors reviewed and edited the content as needed and take full responsibility for the content of the manuscript.

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