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Ranking Women's Well-Being across Countries: A Comparative Analysis Using Preference Selection Index and Artificial Neural Networks

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

One of the most fundamental indicators of a society's level of development is the achievement of gender equality. In countries where equality has been achieved, women's welfare levels have been found to be higher than in other countries. In this study, 12 European countries were evaluated by comparing socio-economic variables specific to women. Given the multidimensional nature of women's well-being, the Preference Selection Index (PSI) and Artificial Neural Network (ANN) methods, which are among the multi-criteria decision-making methods, were used in this ranking process. ANN models were tested in four configurations that varied in weights (equal and factor-based) and target ranking (PSI-based and random) approaches. The resulting country orders were compared. The consistency of ANN generated rankings with the PSI method was evaluated using Spearman rank correlation coefficients. As a result, it can be stated that the PSI method is a reliable

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criterion for assessing women's well-being across countries, and that the ANN model using factor analysis-based weighting yields the closest outcomes to PSI. These results provide a comparative basis that can support broader discussions on women's well-being and evaluations across countries, such as policy considerations aimed at improving socio-economic conditions for women.

Keywords: Preference selection index; artificial neural networks; women's well-being level; country rankings.

1. INTRODUCTION

Today, one of the key indicators used to assess countries' levels of development is the well-being of women. Variables such as women's position in society, their individual contributions to the national economy, and their levels of representation and participation in political life are regarded as critical markers of a country's social development and overall well-being. These dimensions are also emphasized in SIGI 2023 Global Report, which highlights how gender norms continue to shape women's well-being (OECD, 2023). Nevertheless, in many countries, women continue to face unequal opportunities in areas such as education, employment, health, and political representation. Therefore, a comprehensive examination of women's well-being can provide meaningful insights and reveal significant differences in country rankings from academic, social, and political perspectives. As women's well-being is multidimensional, cross-country comparisons require methods that can reflect this complexity. Prior research also shows that women's subjective well-being is closely tied to the broader gender equality context of a country, reinforcing the need for comparative approaches that capture such variation (Meisenberg & Woodley, 2015). For this reason, ranking becomes a suitable approach for identifying relative differences across countries.

There are numerous studies in the literature that analyzed women's well-being, their contributions to society, and their influence on countries' levels of development from a statistical perspective. Uzkurt (2024) examined the factors affecting female employment in Southern European welfare regime countries between 1990 and 2022 using panel data analysis and found that increases in education levels positively influence female employment. Tekkanat and Özkara (2025) used the Global Gender Gap Index to compare Iceland and Turkey and proposed policy recommendations aimed at reducing gender inequality. Turanli et al. (2015) analyzed data from 44 countries covering the period 1990–2010 using panel regression analysis and demonstrated that women's educational attainment and labor force participation rates have significant effects on countries' levels of development. Aycın et al. (2024) analyzed OECD countries using various economic and social variables related to women and ranked them through the ARAS, TOPSIS, and MABAC multi-criteria decision-making methods. In her study, Gërxhani (2020) designed an experimental framework to examine how status ranking affects the performance of men and women and presented empirical findings for Italy, the Netherlands, and Spain.

Studies in the literature have generally analyzed socio-economic variables related to women by applying various ranking techniques and producing comparative country rankings. In this study, indicators related to women obtained from the "How's Life?" and "Gender Inequality Index" reports, which are published annually, were used to rank European countries selected to ensure geographical diversity. In the first stage, the Preference Selection Index (PSI) method was applied, allowing countries to be both ranked and compared with one another. Moreover, unlike many previous studies, this study also employed an Artificial Neural Network (ANN) approach to generate country rankings. During this process, two different weighting schemes (equal weights and factor-analysis-based weights) were constructed, and new rankings were produced both without a reference ranking and based on the PSI results. Finally, all rankings obtained through the PSI and ANN methods were compared, and the selected countries were evaluated according to their levels of women's well-being.

2. METHODOLOGY

In this study, the ranking of countries based on variables related to women will be carried out using the Preference Selection Index (PSI) method, one of the multi-criteria decision-making techniques, and an Artificial Neural Network (ANN) approach that enables ranking using weights.

2.1 Preference Selection Index

The Preference Selection Index (PSI) method, developed by Maniya and Bhatt (2010), is a multi-criteria decision-making technique designed to identify the best alternative without incorporating the relative importance (weights) of the criteria. (Maniya & Bhatt, 2010). In this method, the alternatives under evaluation are assigned a score expressed as a preference index, and they are ranked based on these values (Demirci, 2022). This method, which is mostly applied during the execution of supply processes, has also been used in various applications in literature due to its ease of use and its suitability for situations in which determining criterion weights is difficult. For example, Dua (2025) evaluated different sustainable energy technologies in his study and compared the alternatives using the PSI method. Aksoy and Özbük (2017) highlighted the importance of hotel location selection by ranking several hotels across Istanbul using the PSI method based on various criteria. In addition, Attri and Grover (2015) employed the PSI method while examining the process to be followed for different positions during the design stage of the production process.

In the PSI method, a preference index value is calculated for each alternative, and the rankings are generated based on these index values (Akyüz & Aka, 2017). The following steps are followed during the implementation of the method (Maniya & Bhatt, 2010; Akyüz & Aka, 2017).

Step 1 – Defining the problem: The alternatives and evaluation criteria related to the subject are identified.

Step 2 – Constructing the decision matrix: The data obtained are organized into a decision matrix, as presented below.

Alternatives	**Criteria**			
	C_1	**C_2**	**…**	**C_m**
A_1	x_{11}	x_{12}	…	x_{1m}
A_2	x_{21}	x_{21}	…	x_{2m}
…	…	…	…	…
A_n	x_{n1}	x_{n2}	…	x_{nm}

Here, A_1, A_2, …, A_n represent the alternatives being compared, and C_1, C_2, …, C_m represent the criteria. The term x_{ij} denotes the value of criterion C_j for alternative A_i.

Step 3 – Normalization of the decision matrix: Since the criteria included in the study may be expressed in different units of measurement, the values in the decision matrix are standardized to fall between 0 and 1. If the criterion under consideration is a benefit criterion, it should be normalized using formula (1); if it is a cost criterion, it should be normalized using formula (2).

$$R_{ij} = \frac{x_{ij}}{x_{j,max}} \tag{1}$$

Here $x_{j.max}$ denotes the maximum value for the relevant criterion.

$$R_{ij} = \frac{x_{j,min}}{x_{ij}} \tag{2}$$

Here $x_{j.min}$ denotes the minimum value for the relevant criterion.

Step 4 – Calculation of the preference variance value (PV_j): The preference variance value for each criterion is calculated using the following formula.

$$PV_j = \sum_{i=1}^{n} \left[R_{ij} - \bar{R}_j\right]^2 \tag{3}$$

In the above formula, R_{ij} represents the normalized matrix values, while $\bar{R}_j$ represents the average of the normalized values of criterion j.

Step 5 – Calculation of the total preference value (Ψ_1): To compute this value, the deviation in the preference value (Φ_j) must first be calculated. This value is obtained as shown in formula (4).

$$\phi_j = \left|1 - PV_j\right| \quad (4)$$

Based on this, the total preference value is calculated as follows.

$$\psi_j = \frac{\phi_j}{\sum_{i=1}^{M} \phi_j} \quad (5)$$

Here, the sum of the total preference values calculated separately for all criteria must equal 1. ($\sum_j \psi_j = 1$)

Step 6 – Calculation of the preference index (I_i): The preference index value for each alternative is calculated using the formula given below.

$$I_i = \sum_{i=1}^{M} (R_{ij} \times \psi_j) \quad (6)$$

In the above formula, R_{ij} represents the values in the normalized matrix, while ψ_j represents the total preference values. The alternative with the highest value in the resulting index is regarded as the alternative with the highest performance, and the performance ranking of the alternatives is completed by ordering the index values from largest to smallest.

2.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are an artificial intelligence approach based on the theory that the functioning of biological neurons can be modeled through mathematical functions. This theory was first introduced by McCulloch and Pitts (1943), who developed the first mathematical neuron model, known as the McCulloch-Pitts (MP) neuron. Building on this foundation, Rosenblatt (1958) proposed the Perceptron, the first functional model based on a single-layer feedforward architecture, thereby providing an implementable learning algorithm and transforming ANNs from an abstract theoretical concept into a computational model. Research on ANNs that began with the MP neuron and became more concrete with the Perceptron, led to various architectural and algorithmic advancements in subsequent decades.

In particular, the Rectified Linear Unit (ReLU) activation function, which became prominent in the 2010s, accelerated the learning process and enabled deep neural networks to be applied to more complex tasks (Krizhevsky, Sutskever, & Hinton, 2012). Dikici and Altuntaş (2023) employed the ReLU activation function in their ANNs model developed for classifying protein folding types. Similarly, Bougteb et al. (2023) utilized the ReLU activation function to model nonlinear relationships among multiple criteria in recommendation systems.

The range of the ReLU activation function is [0, ∞), and the function is defined as follows:

$$f(x) = \max(0, x) \quad (7)$$

Another activation function used in the model output for classification tasks is the Sigmoid function. Since its outputs are constrained between 0 and 1, it is commonly employed in binary classification problems (Dubey et al., 2022). The Sigmoid function is defined below.

$$f(x) = \frac{1}{1+e^{-x}} \quad (8)$$

Compressing the output values of the sigmoid function between 0 and 1 enables the scores generated by the model to be used directly for ranking purposes (Dubey et al., 2022; Jagtap & Karniadakis, 2023)

In an ANN structure, optimization algorithms are employed to minimize the loss function during the model training process. Gradient descent (GD) is the primary optimization method that forms the basis of the learning process in ANN models (Amari, 1998). GD updates the network weights step by step to minimize the model error and aims to find the point at which the loss function reaches its minimum value. In this process, a learning rate is defined, and at each iteration, the weights are updated in the direction that reduces the error by an amount proportional to this rate. Let η denote the learning rate, w the weight, and L the loss function value; GD is computed as follows:

$$w_{new} = w_{old} - \eta \frac{\partial L}{\partial w} \quad (9)$$

Loganathan and Latha (2025) compared the performance of different optimization algorithms in classifying OCT images for the diagnosis of retinal disease and the study demonstrated that the Adam algorithm achieved the highest performance in terms of accuracy and error across models with different architecture. The Adam optimization algorithm is an advanced variant of the GD method and minimizes the loss function in a balanced manner through dynamic updates (Kingma & Ba, 2015).

Cross-validation methods are employed in ANN models to increase the reliability of the obtained results and to evaluate the model's generalization capability. During cross-validation, the dataset is divided into multiple parts, and the model is tested separately on each part. This ensures that the model is evaluated not only on observations used during training but also on unseen data (Hastie et al., 2009).

LOOCV (Leave-One-Out Cross Validation), a cross-validation technique, leaves each observation in the dataset as the test set while using the remaining n-1 observations for training. By repeating this process n times—once for each observation—every observation is independently predicted by the model. The formula for the LOOCV method is given below.

$$\hat{y}_i = f^{(-i)}(x_i), i = 1, \ldots, n. \quad (10)$$

For this reason, in studies with a limited number of samples, the LOOCV method provides an unbiased and reliable performance estimate by including every observation in the evaluation process. (Arlot & Celisse, 2010).

3. RESULTS AND DISCUSSION

There is extensive literature on women's rights, women's living standards, and social welfare. In this study, which aims to assess the living standards of women in European countries, the selected European countries were compared using various criteria.

The criteria used to compare the countries in the study are presented in Table 1. The data were obtained from the How's Life (2024) and Gender Inequality Index (2025) reports (UNDP, 2025) (OECD, 2024).

The selected countries and the data related to these countries are presented in Table 2. When constructing this sample of European countries, a total of 12 countries were considered to publish up-to-date and complete statistics to avoid issues arising from missing data, and that represent different regions of Europe to ensure geographical diversity.

Table 1. The criteria and their descriptions

Criterion No	Criterion	Description
C1	Employment Rate (Women)	Percentage of women aged 25–64
C2	Life Satisfaction (Women)	0-10 scale
C3	Job Satisfaction (Women)	0-10 scale
C4	Parliamentary Representation (Women)	Average of quarterly ratios
C5	Life Expectancy at Birth (Women)	Years
C6	Feeling Unsafe at Night (Women)	Percentage of the population aged 15 and over
C7	Long Working Hours (Women)	Percentage of employees
C8	Lack of Social Support (Women)	Percentage of the population aged 15 and over
C9	Long-term Unemployment Rate (Women)	Percentage of the labor force

Table 2. Selected countries (Alternatives) and their values by criteria (Decision Matrix)

Alternatives	C1 max	C2 max	C3 max	C4 max	C5 max	C6 min	C7 min	C8 min	C9 min
Belgium	71.38	7.60	7.70	42.70	84.60	36.39	2.19	10.06	1.80
Denmark	78.23	7.60	7.60	43.70	83.80	21.06	0.86	4.93	0.49
Estonia	82.17	7.20	7.70	29.20	83.10	17.79	1.03	6.38	1.49
Finland	79.80	7.80	7.80	45.88	84.40	19.41	1.30	3.25	1.21
France	73.39	7.10	7.00	37.90	85.90	28.47	4.16	13.96	1.70
Greece	59.71	6.80	6.80	22.00	84.20	46.33	2.25	14.12	8.81
Italy	58.97	7.20	7.30	31.80	85.80	39.72	2.47	13.84	4.84
Latvia	77.47	6.90	7.70	29.75	80.80	28.41	0.46	6.72	1.64
Netherlands	79.49	7.60	7.70	37.93	83.40	25.52	0.70	7.37	0.55
Portugal	78.41	7.00	7.20	36.75	85.20	22.02	4.52	12.26	2.65
Slovenia	76.66	7.70	7.70	37.53	85.00	13.84	2.09	7.71	1.37
Spain	67.82	7.20	7.30	43.58	86.70	21.96	1.53	8.31	5.09

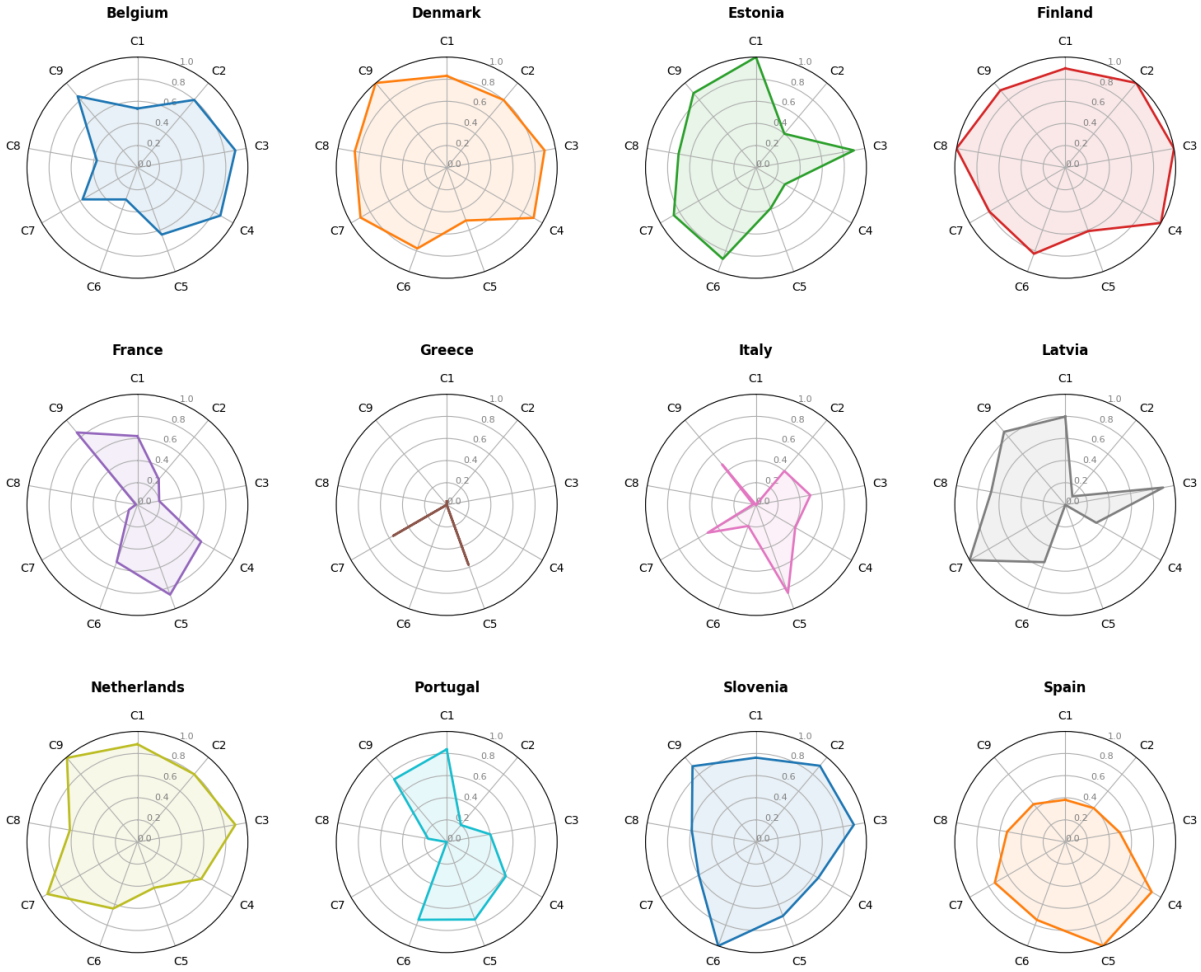


Fig. 1. Radar charts showing the normalized performance of 12 countries across the nine women's well-being criteria (C1–C9). All indicators normalized to a 0–1 scale for comparability

Fig. 1 presents the radar charts of the 12 European countries based on the criteria used in the analysis. All indicators, benefit and cost, were normalized to ensure comparability across criteria and across countries, with higher values representing better performance.

The radar profiles highlight the multidimensional nature of the variables and reveal clear cross-country differences. Some countries, such as Finland, Denmark and Slovenia, display relatively balanced and high performance across several dimensions, while others show uneven or consistently lower values.

3.1 Preference Selection Index Application

The countries listed in Table 2 and their corresponding values constitute the decision matrix used for applying the PSI method. After the decision matrix was normalized as described in Step 3 of the method explanation, the preference variance values were calculated and are presented in Table 3.

In the subsequent stage of the study, the total preference values were computed as specified in Step 4 of the method section, and the results are shown in Table 4.

Table 3. Preference variance values for the criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Preference Variance Values	0.098	0.021	0.020	0.268	0.004	0.436	0.765	0.544	0.975

Table 4. Total preference values for the criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9	Total
$\lvert 1 - PV_j \rvert$	0.902	0.979	0.980	0.732	0.996	0.564	0.235	0.456	0.025	5.871
Total Preference Values	0.154	0.167	0.167	0.125	0.170	0.096	0.040	0.078	0.004	1.000

Table 5. Preference index values and rankings

	C1 max	C2 max	C3 max	C4 max	C5 max	C6 min	C7 min	C8 min	C9 min	Total (index)	Rank
Belgium	0.133	0.163	0.165	0.116	0.166	0.037	0.008	0.025	0.001	0.814	8
Denmark	0.146	0.163	0.163	0.119	0.164	0.063	0.021	0.051	0.004	0.894	2
Estonia	0.154	0.154	0.165	0.079	0.163	0.075	0.018	0.040	0.001	0.848	5
Finland	0.149	0.167	0.167	0.125	0.165	0.069	0.014	0.078	0.002	0.935	1
France	0.137	0.152	0.150	0.103	0.168	0.047	0.004	0.018	0.001	0.781	10
Greece	0.112	0.145	0.146	0.060	0.165	0.029	0.008	0.018	0.000	0.682	12
Italy	0.110	0.154	0.156	0.086	0.168	0.033	0.007	0.018	0.000	0.735	11
Latvia	0.145	0.148	0.165	0.081	0.158	0.047	0.040	0.038	0.001	0.822	7
Netherlands	0.149	0.163	0.165	0.103	0.163	0.052	0.026	0.034	0.004	0.859	4
Portugal	0.147	0.150	0.154	0.100	0.167	0.060	0.004	0.021	0.001	0.803	9
Slovenia	0.143	0.165	0.165	0.102	0.166	0.096	0.009	0.033	0.002	0.880	3
Spain	0.127	0.154	0.156	0.118	0.170	0.061	0.012	0.030	0.000	0.829	6

Using the formula described in the Method section (6), preference index values were calculated for all countries, and the results are presented in Table 5.

The index values obtained for the countries were ranked from highest to lowest to evaluate women's well-being based on the criteria examined. According to this ranking, Finland occupies the highest position among the countries studied in terms of the level of well-being and safe living conditions provided for women. Finland is followed by Denmark and Slovenia. Among the 12 countries analyzed, the three countries with the lowest index values are France, Italy, and Greece, respectively.

3.2 Artificial Neural Network Model Application

At this stage of the study. an ANN model was employed to compare the countries. The criteria listed in Table 1 were used as input variables, and the model was trained using an output (target) variable representing the ranking of the countries. For country comparison, a fully connected ANN model with two hidden layers was utilized in this study. The components of the model architecture, including the number of criteria used in the input layer, the structure of the hidden layers, the activation functions, and the training parameters, are presented in Table 6.

Table 6. Parameters used in the ANN model

Parameters	Specifications
Input Layer	9 neurons (9 criteria)
1st Hidden Layer	16 neurons. ReLU activation
2nd Hidden Layer	8 neurons. ReLU activation
Output Layer	1 neuron. Sigmoid activation
Network Structure	Fully connected feed-forward architecture
Loss Function	Mean Squared Error (MSE)
Optimizer	Adam. learning rate = 0.001 (default)
Batch Size	2
Number of Epochs	300 (early stopping enabled)
Early Stopping	30 epochs. no improvement in weight updates
Evaluation Method	Leave-One-Out Cross Validation (LOOCV)

The number of neurons used was randomly selected within the minimum and maximum limits recommended by Heaton (2008). The batch size was set to 2 to accommodate the small dataset, allowing the network weights to be updated more frequently. The number of epochs was set to 300; however, to maintain training performance, unnecessary iterations were avoided by employing the early stopping method.

In the first stage of the ANN application, equal initial weights were assigned to the criteria used. At this stage, the ANN model was trained twice independently—once using a randomly generated ranking as the target variable and once using the ranking obtained through the PSI method. In the second stage, the same two rankings were used again; however, instead of equal initial weights, the factor loadings obtained from the factor analysis (applied to capture the relationships among the criteria) were assigned as the initial weights.

Consequently, the ANN model produced four different rankings by combining two weighting schemes (equal weights and factor analysis–based weights) with two target ranking types (PSI-based and random), as shown below:

1. Equal weights, PSI ranking (EW-PSI)
2. Factor weights, PSI ranking (FW-PSI)
3. Equal weights, Random ranking (EW-RR)
4. Factor weights, Random ranking (FW-RR)

By including the ranking calculated using the PSI method in Table 5 (PSI Rank), a total of five different rankings were obtained and presented in Table 7.

Based on the assumptions supported by expert opinion that the PSI ranking represents the most accurate ordering, the extent to which the rankings generated by ANN models resemble the PSI ranking was examined. Countries whose ANN-generated rankings coincide with those obtained through the PSI method can be identified in Table 7. Models that used the PSI ranking as the target variable (EW-PSI and FW-PSI) demonstrated a high level of consistency with the PSI Rank, whereas randomly targeted models (EW-RR and FW-RR) showed substantial deviations from the PSI Rank.

Countries ranked at the top—such as Finland, Denmark, and Slovenia—match the PSI Rank perfectly in PSI-targeted models, while randomly targeted models shift countries such as Greece and Portugal to higher positions. As illustrated here, ANN models are trained according to the target variable, using a random ranking in the absence of prior information negatively affects model performance and leads to a noticeable decline in ranking accuracy. Overall, the FW-PSI model emerges as the most consistent and reliable ranking model, given its structural weighting and alignment with the target ranking.

To quantitatively assess the similarity among the obtained rankings, the relationships between the five different rankings were analyzed using the Spearman rank correlation coefficient (ρ). In this way, the consistency of the rankings relative to the ordering obtained through the PSI method was statistically examined, and the results are presented in Table 8.

Table 7. Country rankings obtained using the PSI method and ANN models

	PSI Rank	EW-PSI	FW-PSI	EW-RR	FW-RR
Finland	1	1	1	6	5
Denmark	2	2	2	9	9
Slovenia	3	3	3	5	4
Netherlands	4	4	5	4	6
Estonia	5	5	4	10	10
Spain	6	9	8	7	1
Latvia	7	7	7	8	8
Belgium	8	6	6	3	3
Portugal	9	8	9	2	2
France	10	11	10	11	12
Italy	11	12	12	12	11
Greece	12	10	11	1	7

Table 8. Spearman rank correlations between PSI and ANN-based rankings

	PSI Rank	EW-PSI	FW-PSI	EW-RR	FW-RR
PSI Rank	1	0.930	0.958	-0.056	0.217
EW-PSI	0.930	1	0.979	0.182	0.245
FW-PSI	0.958	0.979	1	0.035	0.189
EW-RR	-0.056	0.182	0.035	1	0.720
FW-RR	0.217	0.245	0.189	0.720	1

When examining Table 8, the other four rankings must be evaluated relative to the ranking obtained using the PSI method, assuming that the PSI ranking is the closest approximation to the true ordering. The results show a very high level of positive correlation between the PSI ranking and the PSI-targeted ANN models (EW-PSI and FW-PSI). This indicates that when the PSI ranking is used as the target variable, the models can largely reproduce the ranking and achieve high rank consistency (ρ=0.93 and ρ=0.96). In contrast, the correlation values between the PSI ranking and the randomly targeted models (EW-RR and FW-RR) are considerably low (ρ= –0.06 and ρ=0.22). This finding demonstrates that randomly specifying the target variable fails to provide any structural guidance during the ANN learning process, thereby weakening the consistency of the generated rankings with the PSI ranking. Furthermore, the use of weights obtained from factor analysis contributed to the ranking results being closer to the PSI ranking, as these weights better reflect the relative importance of the criteria compared to models using equal weights.

4. CONCLUSION

Gender equality is one of the most important indicators of a society's level of well-being and development. Countries in which women are supported socioeconomically and culturally and enjoy high levels of well-being tend to demonstrate substantially higher levels of development compared to others. For this reason, many studies examining societal well-being in literature incorporate variables related to women's socioeconomic indicators.

In this study, variables expressing the socioeconomic status of women were obtained from the OECD's How's Life? (2024) and the UNDP's Gender Inequality Index (2023) reports. The European countries selected for comparison were chosen to represent different regions of Europe and to avoid missing data issues. This research aimed to compare women's well-being levels among European countries using both the Preference Selection Index (PSI) method and Artificial Neural Network (ANN) models. According to the PSI method, the countries with the highest levels of women's well-being are Finland, Denmark. and Slovenia. Distinct from previous studies in literature, this research also ranked countries using ANN models. The ANN models were applied in four configurations combining different weighting and target-ranking approaches (equal vs. factor weights; PSI-based vs. random targets). The models that used the PSI ranking as the target variable showed high consistency with the PSI results. Weighting based on factor analysis better reflected the relative importance of the criteria and, under the assumption that the PSI ranking represents the most accurate order, produced the most successful ranking performance. In contrast, models trained using random target rankings deviated substantially from the PSI ordering. These findings were further supported by Spearman rank correlation analysis.

When expert opinions are considered, the results indicate that the PSI method is a reliable tool for ranking countries in terms of women's well-being, and that ANN models, particularly when factor analysis–based weighting is used, yield highly consistent and robust results. The comparative results indicate that combining traditional methods with machine-learning models can yield consistent outcomes. It should be noted that ANN models require a defined target ranking for supervised learning, and PSI was selected as a reference based on methodological considerations to ensure analytical consistency. One limitation of this study is the small sample size, which restricts the generalizability of ANN-based findings despite the use of cross-validation methods. Future studies may enhance such analyses by incorporating additional indicators related to justice, safety and gender equality to improve the overall assessment of women's well-being.

In conclusion, ANN models can provide successful and complementary outcomes when used alongside traditional methods.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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