Artificial Intelligence and Organizational Sustainability: Neural Network Modeling for Probability-Based Scoring

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Abstract. *In the context of increasing environmental and social responsibility concerns, organizations are looking for innovative methods to assess and improve sustainability performance. This study explores the role of artificial intelligence (AI) – neural networks, in developing a probability-based evaluation system for organizational sustainability score. Traditional evaluation methods frequently rely on pre-established performance indicators, which can introduce subjectivity and inaccuracies. To overcome these limitations, the research proposes a neural network model that integrates economic, social, and environmental dimensions into a structured evaluation framework. The study uses data collected from 30 companies listed on the Bucharest Stock Exchange. The neural network was developed in MATLAB, with a feed-forward structure with two hidden layers and a Levenberg-Marquardt training algorithm. The results – probabilistic organizational sustainability score reflects an intermediate position associated to the analyzed companies, indicating therefore an acceptable compliance level, but also the existence of improvement opportunities; likewise environmental and social dimensions have a stronger influence on organizational sustainability, while the economic dimension, although relevant, has a lower impact. The findings demonstrate that AI-based models offer a more dynamic and objective approach to sustainability assessment, reducing human error and improving the accuracy of predictions. The research contributes to the literature by introducing a structured, data-driven methodology, providing valuable insights for organizational managers and researchers interested in AI-assisted decision-making.*

Keywords: sustainable development, organizational sustainability, neural network, modeling, probability-based score.

Introduction

In "Resilient People, Resilient Planet: A Future Worth Choosing" report the United Nations defined a vision for the sustainability. Hence this involves equitability and a emerging economy that aims to (United Nations, 2012; Sala, 2020): (i) eradicate poverty, reduce inequalities and achieve inclusive development; (ii) increase sustainable production and consumption, reduce climate change and respect various important global limits.

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In a global world where the population is constantly growing, current production systems and consumption behavior, are raising great concerns. These concerns are related to the potential negative environmental impacts. Hence the irrational use various natural resources can raise issues associated with production processes. Therefore, an effective sustainable strategies development should integrate the principles of resource efficiency and eco-innovation, as well as on interconnectivity with the circular economy to ensure a less dissipative resources use (Corrado & Sala, 2018; Sala, 2020; Sarfraz et al., 2022).

Organizations worldwide are seeking innovative methodologies to assess and improve sustainability performance, balancing economic development with environmental responsibility and social impact (Herghiligiu et al., 2024). Startin from the fact that exists environmental and social issues, the artificial intelligence (AI) role in fostering organizational sustainability has become a very important research literature topic. Hence leveraging AI, particularly neural network models, to develop associated score probabilities that facilitate an objective sustainability assessment represents a promising approach.

Sustainability assessment is mostly based on predefined key performance indicators (KPIs) and, respectively, on various qualitative analyses, which can generate subjectivity and inaccuracy (Hubbard, 2009). Likewise, Saad et al., (2023, p. 835) mentioned that "sustainability rating systems currently used are under intense debate due to the lack of interdependency and standardization, and the presence of subjectivity and financial biases"; or Herghiligiu et al., (2024, p. 234) conclude that "organizational sustainability assessment represents a complex statistical approach, presented in the literature as sometimes contradictory and unclear, but characterized by a current need for flexible statistical methods and techniques, which have a wider spectrum of applicability".

The integration of AI – based models, in achieving sustainability, e.g. artificial neural networks, enhance automation and optimization of an evaluation process by identifying complex patterns, improving predictive accuracy and reducing human error (Choudhary et al., 2019). Hence such an approach develops a dynamic and adaptable framework for assessing organizational sustainability.

Even recent studies have demonstrated the AI models effectiveness in assessing organizational sustainability, most existing approaches (e.g. Olawumi & Oladapo, 2025; Alharithi & Alzahrani, 2024), focus on optimizing predictive performance without providing a clear and interpretable framework. Furthermore, traditional evaluation methods, underperform to capture the complex nonlinear relationships between environmental, social and economic dimension. Therefore, this study proposes an approach based on artificial neural networks to model organizational sustainability in a probabilistic framework, thus answering the following research question: "How can AI – artificial neural networks, be used to assess and model organizational sustainability based on a probabilistic approach?"

This paper aims to develop an AI – artificial neural networks framework (using MATLAB 2016a software) for the organizational sustainability assessment process, using representative organizational indicators (associated to financial/ economic, environmental and social sustainability dimensions), in order to obtain an associated score. Hence the main research objective is to develop and validate a model based on AI – artificial neural networks for the organizational sustainability probabilistic assessment (score).

The research purpose is to improve the organizational sustainability evaluation process and therefore to contribute to the literature starting of the fact that Saad et al., (2023, p. 835) argue that "… there is lack of structured methodological frameworks to assess the sustainability performance of companies …" (Herghiligiu et al., 2024).

Hence, starting from previously mentioned research purpose and main objective, this paper mainly aims to: (i) develop a AI – artificial neural networks model for sustainability probability-based scoring, and (ii) test the model's effectiveness using real-world organizations data.

The research results contribute to the literature by developing and validating an AI model based on artificial neural networks, providing an innovative probabilistic approach for organizational sustainability assessment. Compared to existing AI models, which focus on optimizing predictive performance, the proposed model combines the ability to analyze complex nonlinear relationships with a high degree of results interpretability.

Literature review

Organizational sustainability

Organizational sustainability represents a very important "element" of modern management strategies, reflecting the firm's commitment to balance economic/ financial, environmental and social performance – "triple bottom line" (Bocken et al., 2014; Taucean et al., 2019; Pislaru et al., 2019; Herghiligiu et al., 2021; Herghiligiu et al., 2024). This concept involves integrating sustainability into all operational aspects, thus supporting the organization stability and resilience (Geissdoerfer et al., 2017). Thus, a holistic approach requires a continuous assessment regarding the operations impact on all stakeholders and the adaptation of organizational strategies according to the current change's dynamics.

Summarized in Table 1, it can be observed the dimensions and associated subdimension of organizational sustainability.

Table 1. Organizational sustainability

No.	*Dimension*	*Subdimension*
1.	Economic/ financial	profit; employee motivation; efficiency; suppliers' relationships; innovation; marketing practices; ethics in management; risk management; government relations
2.	Social	human resource programs; health and safety; human rights; quality management; local engagement; philanthropy; volunteering; product liability; consumer relationship management; sustainable consumption
3.	Environmental	energy conservation; row materials; H_2O management; waste management; climate change; pollution; production management; supply chain management; green suppliers; environmental risk; environmental reporting; EMS; compliance with environmental requirements

Source: Pislaru et al., 2019; Herghiligiu et al., 2021; Herghiligiu et al., 2024.

The sustainability economic component refers to the organization's profitability on long term while ensuring efficient and responsible use of financial resources (Geissdoerfer et al., 2017).

The environmental component associated to the sustainability integrates the reduction of organizations' negative impact on the environment and the responsible use of natural resources (Saad et al., 2023). Organizations that implement environmental practices not only comply with legal specific regulations, but also improve their image and energy efficiency (Pislaru et al., 2019).

The sustainability social component, as Herghiligiu et al., (2024, p. 235) mentioned, refers to the "… organizational configuration associated with social responsibility which is related to the firm societal relations". In essence this sustainability dimension implies equity, human rights, safe and fair work conditions (Hubbard, 2009).

Evaluation methodologies associated to organizational sustainability

Sustainability assessment is very important for identifying areas (associated dimension) which must be improved and also to demonstrate commitment to actual responsible practices (Hubbard, 2009). Accurate measurement allows organizations to set goals, to monitor progress, and to communicate results to involved parties.

Effective implementation of sustainability measurement faces various obstacles; as Nikolaou et al. (2019, p. 1) mentioned "many of these frameworks suffer from several weaknesses mainly associated with standardization and reliability issues and structural failures".

Organizations must allocate significant resources to collect and analyze relevant data, ensure the accuracy and viability of information, and comply with evolving reporting standards (Vinuesa et al., 2019).

Summarized in Table 2, it can be observed, based on different criteria, various organizational sustainability evaluation methodologies (Nikolaou et al., 2019; Herghiligiu et al., 2024).

Table 2. Methodologies – organizational sustainability evaluation

No.	***Criteria***	***Subdimension***
1.	(i) sustainability dimensions/ aspects evaluation methodology (e.g. environmental, social, triple-bottom-line, and so on);	Methodologies that approach: "environmental performance"; "triple-bottom-line evaluation"; "eco-efficiency performance"; "evaluate social performance".
2.	(ii) units used in assessment;	Methodologies that: "assess organizational sustainability in financial/ non-financial terms"; "assess organizational sustainability integrating financial and non-financial measurement units"; "organizational sustainability evaluation framework in financial measurements units"; "examine organizational sustainability considering the sustainability strategies as "win-win" solutions in addition with financial and environmental performance"; "evaluate organizations environmental sustainability using scores (non-financial units)";
3.	(iii) proposed indicators nature (simple or aggregated indicators).	"measurement systems that propose indicators lists [e.g.: Global Reporting Initiative (GRI)] associated to sustainability specific dimensions performance"; "composite indicators associated to sustainability characteristic aspects"

.Source: Herghiligiu et al., 2024

Measuring organizational sustainability involves the use of diverse methodologies, each with specific advantages and limitations. Traditional models based on performance indicators (e.g. financial and environmental reporting or composite indices), are appreciated for transparency and interpretation. However, these traditional models are rigid and unadaptable some times to particular contexts; likewise, are relatively limited to manage uncertainty and interdependencies between sustainability dimensions/ aspects/ factors (Nikolaou et al., 2019).

In comparison, soft computing techniques – such as fuzzy logic, artificial neural networks, and genetic algorithms – offer a more flexible approach capable of capturing the complexity of real systems (Pislaru et al., 2019). Artificial neural networks models can identify nonlinear patterns in large data sets, improving prediction accuracy and adaptability to in business environment changes (Saad et al., 2023).

Methodology

This research adopts a methodological approach based on statistical analysis. In this regard, the following steps are taken: (i) defining the study population and selecting the analyzed sample, (ii) identifying relevant variables and choosing appropriate analysis models or methods, and (iii) collecting and statistically processing data (Herghiligiu et al., 2019; 2024). By using artificial neural networks, a probabilistic score of organizational sustainability will be calculated, based on the identified dimensions.

Study population and analyzed sample

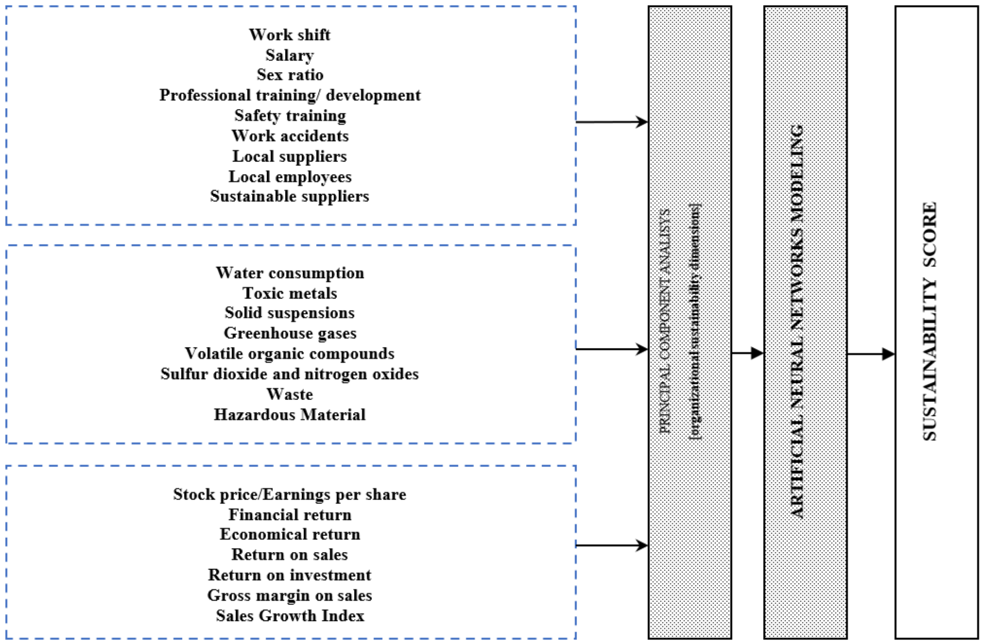
The population analyzed in this study is represented by Romanian large companies listed on the Bucharest Stock Exchange (BSE). For evaluation and modeling, the final selected sample are 30 large companies listed on the BSE; collected associated data are for the interval 2010-2019.

The analyzed sample includes a total of 53 companies, selected for the study, of which: 47 companies from the industrial sector, 6 companies from the service sector, 23 companies for which not all the information necessary for the analysis was available. Thus, the final sample used in the research consists of large 30 companies.

Companies included in the final sample, was selected based on the following relevant criteria (Herghiligiu et al., 2024): (i) companies in insolvency or bankruptcy was excluded; (ii) companies in the banking-financial sector, investment funds, insurance or other financial intermediaries was excluded; (iii) companies for which not all financial, environmental and social (dimensions) information related with the analyzed variables was found, was excluded; (iv) companies for which not all information associated with the analyzed variables was available for the investigated period was excluded.

Relevant variables and appropriate analysis model

Based on the theoretical framework presented, a model for assessing organizational sustainability is proposed (Figure 1). The relevant variables associated with each organizational sustainability dimensions (social, environmental and economic/ financial) and included this evaluation model (Figure 1) are according to the literature (e.g. Pislaru et al., 2019; Herghiligiu et al., 2021; 2024) and with relevant criteria identified in previous literature research (Saad et al., 2023; Herghiligiu et al., 2024). Hence, these relevant criteria are: variables relevance in the sustainability context, statistical significance; variables data availability and quality; variables that have a significant influence on sustainability; variables that could assure model robustness (Saad et al., 2023).



Legend – variable description:

Stock price/ Earnings per share	Reflects the financial market's reaction to the disclosure of the company's net earnings, relative to the total number of issued shares.
Financial return	Relates to the efficiency of capital utilization in connection with net earnings.
Economical return	Assesses the effectiveness of asset utilization in operational activities based on the benefits they generate.
Return on sales	Measures sales performance by considering the recorded net profit margin.
Return on investment	Represents the effectiveness of corporate investments, evaluated through the future cash flows they generate, discounted at the weighted average cost of capital.
Gross margin on sales	Evaluates sales efficiency in terms of the reported gross profit margin.
Sales Growth Index	Determined as the ratio between sales growth over consecutive periods and the sales value in the reference period.
Water consumption	Measures the organization's impact on water resources (m^3).
Toxic metals	Represents the quantity of toxic metals discharged, adjusted for their respective toxicity coefficients.
Solid suspensions	Indicates the average daily discharge of solid suspensions (tons per year).
Greenhouse gases	Accounts for CO_2 equivalentemissions (metric tons).
Volatile organic compounds	Represents the level of emissions related to volatile organic compounds.
Sulfur dioxide and nitrogen oxides	Quantifies SO_2 and NOx emissions.
Waste	Indicates the total mass of solid waste disposed of (tons per unit).
Hazardous Material	Represents the volume of hazardous, harmful, or toxic materials used in production processes.
Eco-design	Percentage of manufactured products incorporating environmentally sustainable design principles.
Recycling rate	Proportion of final products or packaging that has been recycled or discarded.
Work shift	Average number of working hours per week.
Salary	Annual average cost per employee.
Sex ratio	Ratio of female employees to male employees.
Professional training/ development	Proportion of employees who have participated in training programs.
Safety training	Percentage of employees trained in safety and emergency response procedures.
Work accidents	Ratio of work-related injury days to the total number of working days.
Local suppliers	Ratio of local suppliers to the total number of suppliers.
Local employees	Ratio of locally hired employees to the total workforce.
Sustainable suppliers	Percentage of suppliers assessed and selected based on their commitment to sustainability.

Figure 1. Organizational sustainability evaluation model

Source: adapted after Pislaru et al., 2019; Herghiligiu et al., 2021; 2024.

The research variables are integrated in the proposed evaluation model presented and explained in the legend associated to Figure 1.

The data sources used include the GRI, Environmental Protection Agency (EPA), BSE, DataStream Advance, profile websites, and so on. To obtain the estimated results, the data analysis was performed using IBM SPSS 22.0 and MATLAB 2016a.

Principal component analysis (PCA) and AI – artificial neural networks modeling

To identify the main components associated with organizational sustainability, based on (i) the determinants – using principal component analysis (PCA), and (ii) the scores of each component, the three associated representative dimensions were taken into account – Table 1, presented in the literature. Starting from the variables included for each sustainability dimension, the components were determined using PCA, and the parameters of the econometric models correlated with the associated scores were estimated – the results being presented by Herghiligiu et al. (2021; 2024). The scores associated with the three main components of sustainability [economic (financial), environmental, social] follow a normal law, with mean 0 and variance 1 [~ N (0;1)] (Herghiligiu et al., 2024).

Neural modeling is performed in the MATLAB environment, using the modeling tool based on neural networks, its application in research being done to obtain a probability associated to sustainability score.

For this type of organizational sustainability = function (financial; environmental; social) correlation model, a neural network with 2 internal layers [the network is capable of learning nonlinear relationships and is computationally efficient (Raza et al., 2022)], feed-forward type network, with sigmoid transfer function and linear output neurons was used (Vilcu et al., 2018a, b) – Figure 2. The network training algorithm is of the Levenberg-Marquardt (LM) backpropagation type with good properties in terms of solution quality but with limitations to small-sized problems (Norgaard, 2000a, b).

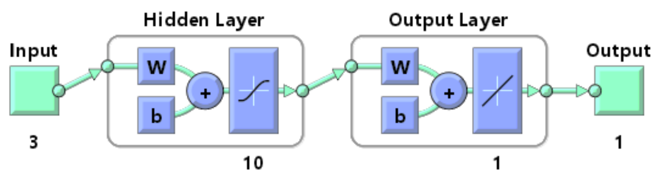


Figure 2. Neural network – organizational sustainability probability score

Source: Authors' own research results/contribution.

The LM algorithm is commonly used in artificial neural networks due to its combination of gradient descent and Gauss-Newton optimization methods (Pooladzandi & Zhou, 2022). LM is ideal for feedforward neural networks used in functional approximation problems, where the goal is to minimize errors (Ali et al., 2022). Compared to other algorithms, LM "is a numerical optimization technique" that could be considered as efficient and viable in various specific assessments associated to sustainability issues (Vlontzos & Pardalos, 2017; Zadmirzaei et al., 2024; Hsu et al., 2025).

Results and discussions

Based on the mentioned organizational sustainability dimensions and on the proposed evaluation model, this section presents the analysis results, focusing not only on the modeling results, but also on providing a possible theoretical motivation that supported these results.

Organizational sustainability main components

Based on the results obtained through PCA the calculation model associated with the organizational sustainability score can be estimated as follows – Equation 1 (Herghiligiu et al., 2024):

$$\begin{aligned} Sustainability\ score &= 0{,}152 \cdot economic\ (financial)\ dimension\ +\ 0{,}520\ environmental\ dimension \\ &+ 0{,}494 \cdot social\ dimension \end{aligned} \quad (1)$$

In light of the coefficients associated with the model (Equation 1), it can be asserted that the organizational sustainability score is positively influenced by two of the analyzed components: the "environmental component" (0.520) and the "social component" (0.494). These two components have a significant influence on the overall sustainability score. In contrast, the "economic component" (0.152) exerts a smaller, but still positive, influence on this score.

These results indicate that environmental and social factors have a significant influence on sustainability scores compared to economic component. This finding aligns with previous literature studies emphasizing the environmental and social governance importance in corporate decision-making (Sarfraz et al., 2022; Khalid et al., 2024; Herghiligiu et al., 2024). Organizations that integrate environmental and social sustainability practices not only comply with regulatory requirements but also improve their reputation, attract investors and enhance long-term resilience (Geissdoerfer et al., 2017).

From a business perspective, the environmental and social dimensions importance may be explained by the increasing regulatory pressures and investor preferences for sustainable business models (Vinuesa et al., 2019). Moreover, studies in the literature highlight that organizations prioritizing sustainability are more likely to achieve competitive advantages (Nikolaou et al., 2019).

Neural network modeling for probability sustainability score

AI – neural network modeling provides a systematic organizational sustainability performance evaluation and improves predictive reliability. Hence a feed-forward neural network was used to model organizational sustainability (Figure 2).

To enhance the neural network generalization, the delaying method associated to the moment of stopping the training stage was used. The values of the input parameters (economic [financial], environmental and social dimensions) were generated after the normalization stage of the values observed in distributions with mean m=0 and standard deviation sigma=1, thus, for each indicator, the mean was taken and sigma was subtracted or added in the parameter definition interval. So, for each input vector, the test values were calculated using the rule of three ς respecting the minimum and maximum values. The data were centralized in Table 3.

Table 3. Sustainability parameter values

Financial = -1.9	Social					Financial = 0	Social				
Environ.	-0.78	0	1	2	2.68	Environ.	0.45	0.45	0.51	0.72	0.72
-1.55	-0.58	-0.41	0.27	0.72	0.72	-1.55	0.23	0.23	0.28	0.72	0.72
-1	-0.50	-0.41	0.27	0.72	0.72	-1	-0.00	-0.00	0.28	0.72	0.72
0	0.00	0.00	0.27	0.27	0.27	0	0.07	0.07	0.28	0.72	0.72
1	0.62	0.62	0.62	0.72	0.27	1	0.58	0.58	0.58	0.72	0.72
2	0.62	0.62	0.62	0.72	0.72	2	0.45	0.45	0.51	0.72	0.72
Financial = -1	Social					Financial = 1	Social				
Environ.	-0.40	-0.40	0.61	0.72	0.72	Environ.	0.51	0.51	0.51	0.72	0.72
-1.55	-0.21	-0.21	0.28	0.72	0.72	-1.55	0.23	0.23	0.28	0.72	0.72
-1	0.21	0.21	0.28	0.72	0.72	-1	0.02	0.02	0.28	0.72	0.72
0	0.21	0.21	0.28	0.72	0.72	0	0.07	0.07	0.28	0.72	0.72
1	0.58	0.58	0.58	0.72	0.72	1	0.58	0.58	0.58	0.72	0.72
2	-0.40	-0.40	0.61	0.72	0.72	2	0.51	0.51	0.51	0.72	0.72

Financial = 3	Social					Financial = 4	Social				
Environ.	-0.78	0	1	2	2.68	Environ.	-0.78	0	1	2	2.68
-1.55	0.72	0.72	0.72	0.72	0.72	-1.55	0.51	0.51	0.51	0.72	0.72
-1	0.72	0.72	0.72	0.72	0.72	-1	0.23	0.23	0.28	0.72	0.72
0	0.72	0.72	0.72	0.72	0.72	0	0.19	0.19	0.28	0.72	0.72
1	0.72	0.72	0.72	0.72	0.72	1	0.19	0.19	0.28	0.72	0.72
2	0.72	0.72	0.72	0.72	0.91	2	0.58	0.58	0.58	2.38	2.39
Financial = 3	Social					Financial = 4.59	Social				
Environ.	-0.78	0	1	2	2.68	Environ.	-0.78	0	1	2	2.68
-1.55	0.72	0.72	0.72	0.72	0.72	-1.55	0.51	0.51	0.51	0.72	0.72
-1	0.72	0.72	0.72	0.72	0.72	-1	0.23	0.23	0.28	0.72	0.72
0	0.72	0.72	0.72	0.72	0.72	0	0.00	-0.00	0.28	0.72	0.72
1	0.72	0.72	0.72	0.72	0.72	1	0.07	0.07	0.28	0.72	0.72
2	0.72	0.72	0.72	0.72	0.91	2	0.58	0.58	0.58	2.38	2.42

Source: Authors' own research results/contribution.

The training vector set, comprising 200 training patterns (Table 3), is divided into three subsets. The first subset, representing 70% of the total vectors, consists of training vectors used to adjust the network's weights and activation thresholds. The second subset, accounting for 15%, includes validation vectors that assess the network's generalization capability and prevent overfitting. During training, the validation error is continuously monitored – initially decreasing, but eventually following an upward trend. If the validation error increases for a predefined number of iterations, the training process is halted to prevent overfitting. The last set of patterns, comprising 15% of the training vectors is used to test the generality of the network – this set is not used in the training phase, its role being to compare different models.

Since the artificial network with 10 neurons did not lead to sufficiently accurate training of the neural network (total correlation coefficient R=0.78), it was decided to increase the number of neurons from 10 to 20 (Jain & Vemuri, 1999).

The results of the neural network training indicators (for the internal structure with 20 neurons per hidden layer) are presented in Figure 3.

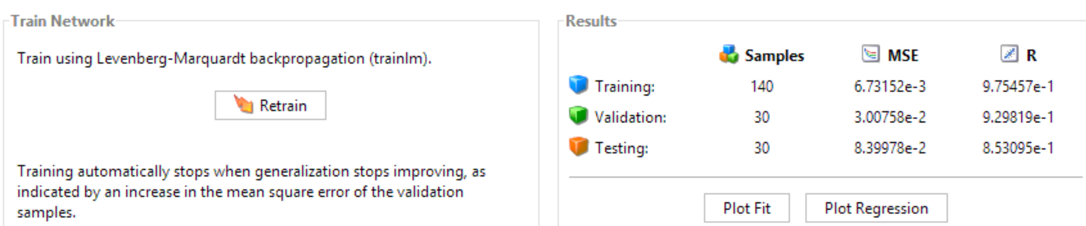


Figure 3. Values of the correlation parameters R and the mean square error – after training

Source: Authors' own research results/contribution.

The internal structure values of the network stabilized after 20 iterations, with an optimal performance obtained at iteration 19 (Figure 4). The training process is halted when the validation error fails to decrease for three consecutive iterations. Figure 4 illustrates the training, validation, and test errors. From this figure, we can conclude that the training process yields good results because the final mean square error is low and all three graphs exhibit a similar pattern, indicating consistency across the training phases; after the 19^{th} training stage the over-fitting phenomenon does not show a major effect.

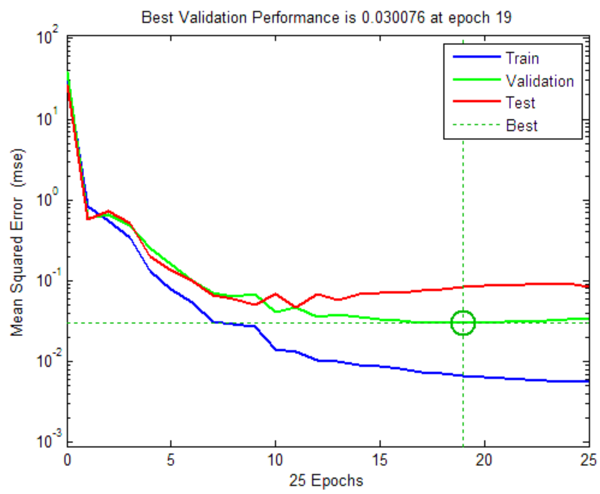
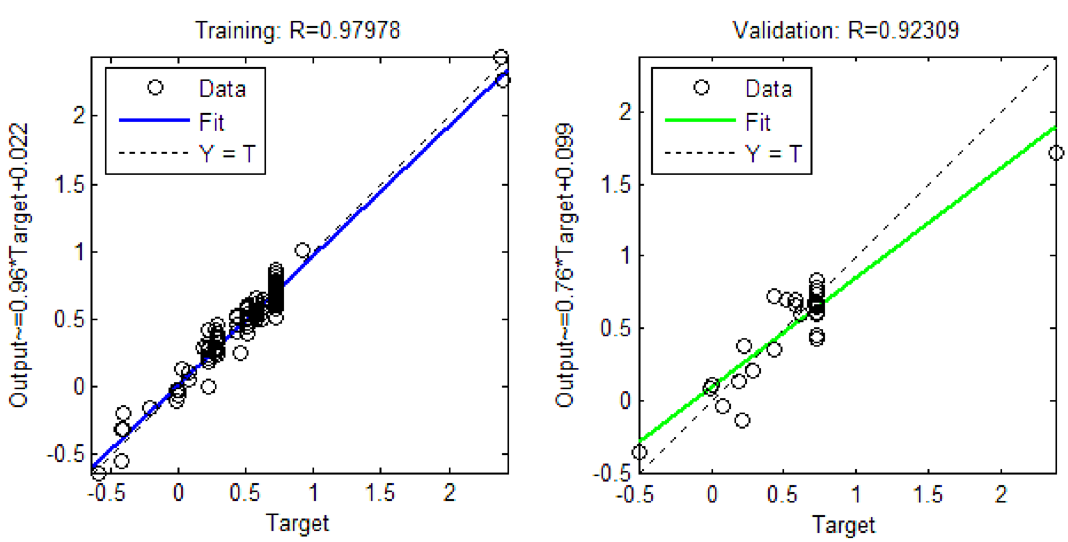


Figure 4. Training, validation and testing errors in the training stage

Source: Authors' own research results/contribution.

Figure 5 shows regression plots for the training, validation, test, and all combined data sets. Each plot compares the target values (Target) with the neural network output values (Output), and the correlation coefficient *R* indicates how well the model fits the data (training (R = 0.97978): the network trained well, the estimated values are very close to the real ones; validation (R = 0.92309): the model generalizes well on the validation data; test (R = 0.8531): the performance is lower on the test set, but remains acceptable; all (R = 0.93096): the overall correlation coefficient is high, indicating a well-adjusted model). The obtained model is performing well, with a high correlation coefficient at all stages. The slight differences between the validation and test sets suggest a possible slight overfitting, but overall, the results are good.

Likewise for a perfect fit of the neural network output over the set of sustainability values, the slope of the plot should be 1 (the plot forms an angle of 45 degrees with the horizontal), which is equivalent to an R value of approximately 0.9.



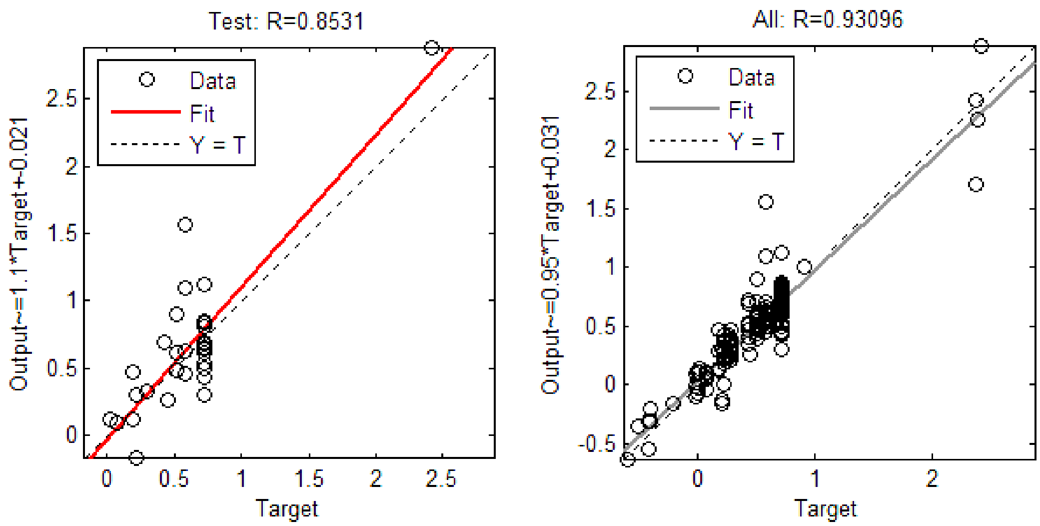


Figure 5. Regression coefficient values and output value graphs

Source: Authors' own research results/contribution.

The neural network is tested on the same set of data (Figure 6) and the output graph is plotted (Figure 7).

Figure 6 shows the results of testing a neural network, indicating two key parameters for evaluating the model's performance: (i) MSE (Mean Squared Error) = 2.18231e-2; this is the mean squared error, which measures the average difference between the actual and predicted values. A small value indicates a well-trained model. (ii) R (Correlation Coefficient) = 0.930553; this coefficient measures the correlation between the predicted and actual values. A value close to 1 suggests a good model fit. Hence the MSE has a small value, which means that the model errors are reduced. The correlation coefficient $R = 0.93$; this value indicates a strong relationship between the network predictions and the actual values, suggesting a good performance of the neural network.

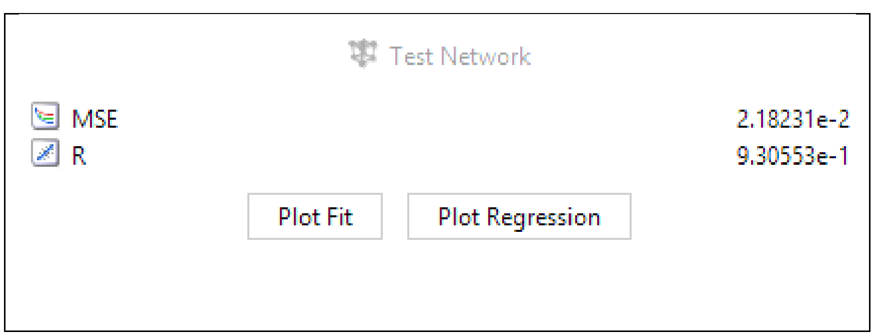


Figure 6. Testing the neural network

Source: Authors' own research results/contribution,

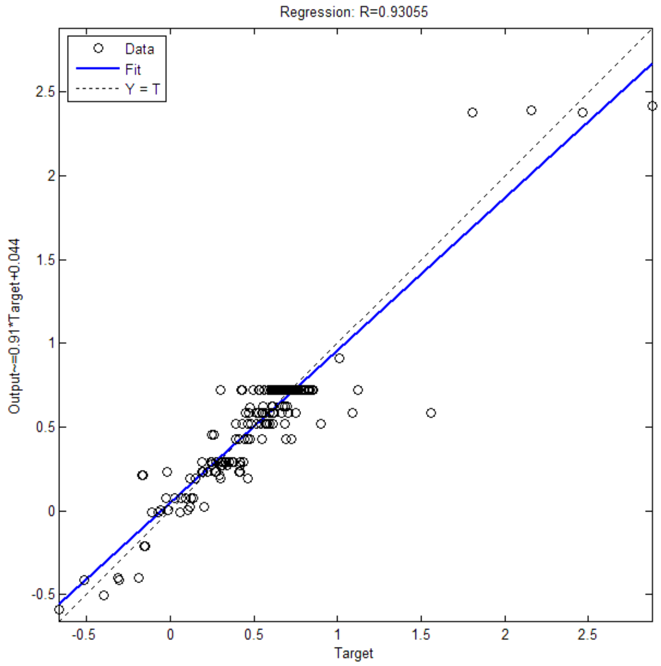


Figure 7. Graph of neural network output associated to the input data set
Source: Authors' own research results/contribution.

Figure 7 shows the regression plot of the neural network used, with a correlation coefficient R = 0.93055 (were X-axis (Target): actual values of the output variable. Y – axis (Output): estimated values of the neural network. Circular dots (Data): individual observations. Blue line (Fit): regression line based on the model predictions. Dotted line (Y = T): ideal line where predictions are identical to actual values). The high correlation coefficient (R = 0.93055) indicates a good fit of the model, suggesting that the neural network predicts the actual values well. The blue regression line is close to the ideal line $Y = T$, indicating a strong correlation between the model outputs and the target values.

```
>> output=sim(RN_sus,set_test)

output =

    0.3185
```

Figure 8. Organizational sustainability score - neural network modeling result
Source: Authors' own research results/contribution.

A simulation of the neural network is executed with the data set of interest; the value generated is 0.3185 (Figure 8). This value represents the probabilistic score of organizational sustainability, being in the interval [− 1.012, 2.459], interval determined by a fuzzy inference system (Herghiligiu et al., 2024). This result reflects the level of sustainability of the organization, suggesting an intermediate position within the defined scale, where negative values indicate a low sustainability level, and higher ones suggest a high sustainable performance.

The probabilistic score of organizational sustainability obtained reflects an intermediate position associated to the analyzed companies, indicating therefore an acceptable compliance level, but also the existence of improvement opportunities. Factors such as regulations, corporate strategies, industry particularities and assessment methodology may explain why companies do not reach high values within the defined scale. To increase this score, would be necessary investments in proactive sustainable practices, integration of advanced social responsibility policies and better environmental impact management.

The proposed neural network-based sustainability assessment model aligns with recent advancements in AI-driven sustainability evaluation frameworks. Researches such as Olawumi & Oladapo (2025) and Alharithi & Alzahrani (2024) emphasize the AI role in improving sustainability assessment by reducing biases associated with human judgment and conventional approaches. While previous studies have focused on predictive accuracy (e.g. Khalid et al., 2024), our model integrates a probabilistic scoring approach.

Compared to conventional scoring models (e.g. Raza et al., 2022), which are based on structured financial disclosures, our approach enhances a more dynamic representation associated to sustainability performance. Moreover, previous AI models have been applied in narrow sustainability aspects (e.g. Zadmirzaei et al., 2024; Vlontzos & Pardalos, 2017), whereas our study provides a comprehensive, multi-dimensional assessment across all three sustainability pillars.

Conclusion

This study highlights the importance of using AI – artificial neural networks, to assess organizational sustainability. The research demonstrates that traditional methods of measuring sustainability are often rigid and susceptible to subjectivity, and the integration of AI-based models can provide a more precise and objective assessment. By using a neural network model trained in MATLAB, the paper proposes a methodology for calculating a probabilistic sustainability score, based on three fundamental dimensions: economic, social and environmental.

The results obtained show that the environmental and social dimensions have a stronger influence on organizational sustainability, while the economic dimension, although relevant, has a lower impact. The probabilistic score of organizational sustainability (0.3185) obtained reflects an intermediate position associated to the analyzed companies, indicating therefore an acceptable compliance level, but also the existence of improvement opportunities.

The proposed model was tested on a dataset associated to companies listed on BSE, and the neural network used demonstrated a high correlation between the estimated and real values, thus confirming the proposed approach validity.

From a methodological perspective, the research validates the use of neural networks for organizational sustainability modeling. On a practical level, the study provides a valuable tool for decision makers (e.g. organizational managers), facilitating data-driven decision-making and optimizing organizational sustainability strategies. Thus, the research reduces the gap between academic theories and the practical applicability of AI in organizational sustainability assessment, contributing to the literature and also to the development of effective future solutions associated to the business environment.

In synthesis, this research contributes to the literature by developing an innovative methodology for assessing organizational sustainability, providing a new perspective on the use of AI in sustainable management.

In the future, developing this model, by including new variables and testing on a larger sample of companies, could help improve its accuracy and applicability. Likewise, these findings

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highlight the necessity of further benchmarking with alternative AI architectures, such as transformer-based sustainability models or hybrid AI – Machine Learning approaches.

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