p-ISSN: 2708-2474
e-ISSN: 2708-2482

www.gmsrjournal.com
GMSR
Global Management Sciences Review
managing humanity

GMSR

GLOBAL MANAGEMENT SCIENCES REVIEW

HEC-RECOGNIZED CATEGORY-Y

VOL. X, ISSUE IV, FALL (DECEMBER-2025)

DOI (Journal): 10.31703/gmsr
DOI (Volume): 10.31703/gmsr.2025(X)
DOI (Issue): 10.31703/gmsr.2025(X-IV)

Double-blind Peer-review Research Journal
www.gsrjournal.com

HumanityPublications
sharing research

Humanity Publications (HumaPub)

www.humapub.com

Doi:https://dx.doi.org/10.31703

Article title

AI Modelling Revisiting Relationship Between Renewable Energy Financing and Environmental Degradation

Abstract

Renewable energy financing (RNEF) has turned into a major factor of sustainable development in response to the growing threat of climate change. In this paper, the effects of RNEF on the environmental degradation (END) in OECD countries during the first quarter of the year 2000 and the fourth quarter of 2024 using an advanced FES-based AI model will be analyzed. The overall conclusion is that the growth of RNEF significantly reduces END statistically as it reduces carbon emissions, which is one of the few aspects in this study that identifies the differences with other studies and contributes to the current literature. The findings offer some insights to the governments of the countries with resource-rich economies, in formulating the effective policies towards realizing the sustainable environmental goals.

Keywords: Renewable Energy Financing, Fuel-Based Energy Consumption, Environmental Degradation, Fes-Based Ai Modelling.

Authors:

Rabia Akram: (Corresponding Author)
College of Management Sciences and Engineering, Shandong University of Finance and Economics, Shandong, China.
Email: (rabiaakram177@gmail.com)

Pages: 77-95
DOI:10.31703/gssr.2025(X-IV).06
DOI link: https://dx.doi.org/10.31703/gmsr.2025(X-IV).06
Article link: http://www.gmsrjournal.com/article/ai-modelling-revisiting-relationship-between-renewable-energy-financing-and-environmental-degradation
Full-text Link: https://gmsrjournal.com/fulltext/ai-modelling-revisiting-relationship-between-renewable-energy-financing-and-environmental-degradation
Pdf link: https://www.gmsrjournal.com/jadmin/Auther/31rvlolA2.pdf

Global Management Science Review

p-ISSN: 2708-2474 e-ISSN: 2708-2482
DOI(journal): 10.31703/gmsr
Volume: X (2025)
DOI (volume): 10.31703/gmsr 2025(X)
Issue: IV (Fall-December 2025)
DOI(Issue): 10.31703/gmsr.2025(X-IV)

Home Page
www.gmsrjournal.com

Volume: X (2025)
https://www.gmsrjournal.com/Current-issues

Issue: III-Summer (September-2025)
https://www.gmsrjournal.com/issue/9/4/2025

Scope
https://www.gmsrjournal.com/about-us/scope

Submission
https://humaglobe.com/index.php/gmsr/submissions

Google Scholar

Humanity Publications (HumaPub)
www.humapub.com
Doi:https://dx.doi.org/10.31703

Citing Article

06	AI Modelling Revisiting Relationship Between Renewable Energy Financing and Environmental Degradation		
Authors	Rabia Akram	DOI	10.31703/gmsr.2025(X-IV).06
		Pages	77-95
		Year	2025
		Volume	X
		Issue	IV

Referencing & Citing Styles

APA	Akram, R. (2025). AI Modelling Revisiting Relationship Between Renewable Energy Financing and Environmental Degradation. *Global Management Sciences Review*, *X*(IV), 77-95. https://doi.org/10.31703/gmsr.2025(X-IV).06
CHICAGO	Akram, Rabia. 2025. "AI Modelling Revisiting Relationship Between Renewable Energy Financing and Environmental Degradation." *Global Management Sciences Review* X (IV):77-95. doi: 10.31703/gmsr.2025(X-IV).06.
HARVARD	AKRAM, R. 2025. AI Modelling Revisiting Relationship Between Renewable Energy Financing and Environmental Degradation. *Global Management Sciences Review,* X, 77-95.
MHRA	Akram, Rabia. 2025. 'AI Modelling Revisiting Relationship Between Renewable Energy Financing and Environmental Degradation', *Global Management Sciences Review*, X: 77-95.
MLA	Akram, Rabia. "Ai Modelling Revisiting Relationship between Renewable Energy Financing and Environmental Degradation." *Global Management Sciences Review* X.IV (2025): 77-95. Print.
OXFORD	Akram, Rabia (2025), 'AI Modelling Revisiting Relationship Between Renewable Energy Financing and Environmental Degradation', *Global Management Sciences Review,* X (IV), 77-95.
TURABIAN	Akram, Rabia. "Ai Modelling Revisiting Relationship between Renewable Energy Financing and Environmental Degradation." *Global Management Sciences Review* X, no. IV (2025): 77-95. https://dx.doi.org/10.31703/gmsr.2025(X-IV).06.

e-ISSN: 2708-2482 Volume: X (2025) Issue: IV-Fall (December-2025) p-ISSN: 2708-2474

Global Management Sciences Review
www.gmsrjournal.com
DOI: http://dx.doi.org/10.31703/gmsr

Pages: 77-95 URL: https://doi.org/10.31703/gmsr.2025(X-IV).06 Doi: 10.31703/gmsr.2025(X-IV).06

Title

AI Modelling Revisiting Relationship Between Renewable Energy Financing and Environmental Degradation

Abstract

Renewable energy financing (RNEF) has turned into a major factor of sustainable development in response to the growing threat of climate change. In this paper, the effects of RNEF on the environmental degradation (END) in OECD countries during the first quarter of the year 2000 and the fourth quarter of 2024 using an advanced FES-based AI model will be analyzed. The overall conclusion is that the growth of RNEF significantly reduces END statistically as it reduces carbon emissions, which is one of the few aspects in this study that identifies the differences with other studies and contributes to the current literature. The findings offer some insights to the governments of the countries with resource-rich economies, in formulating the effective policies towards realizing the sustainable environmental goals.

Keywords: Renewable Energy Financing, Fuel-Based Energy Consumption, Environmental Degradation, Fes-Based Ai Modelling

Authors:

Rabia Akram: (Corresponding Author)
College of Management Sciences and Engineering, Shandong University of Finance and Economics, Shandong, China.
Email: (rabiaakram177@gmail.com)

Contents

- Introduction
- Literature Review
- Empirical Data and Research Methodology
- Experimental Results
- Fes-Based Ai Model Findings
- Conclusion
- Funding
- Declaration About Generating Ai
- Credit Authorship Contribution Statement
- Competing interests
- Acknowledgements
- Appendix A
- References

Introduction

There is a great agreement among the researchers of the fields of energy, environment and economics that global warming poses great dangers to the health of human beings and sustainability of the environment a2023nd equity between generations (Sadorsky, 2011). The diminution of Greenhouse Gas (GHG) emissions, which is the leading cause of the rising global temperatures, has been viewed as a key priority to be addressed by the international authorities in order to avoid a global ecological disaster (Mundaca et al., 2021). It has been predicted that without substantial action, the levels of greenhouse gases in the atmosphere might exceed those of 2035 (Du, 2023), a pattern that the Paris Agreement (2016) directly relates to an increase in the average global temperature exceeding 2C. Going further beyond this climate marker as already emphasized by a general science consensus of more than the Intergovernmental Panel on Climate Change (IPCC, 2007) would cause significant and potentially irreversible consequences. They consist of drastic loss of biodiversity, high increases in the sea level, increased extreme weather, prolonged droughts, and major reductions in freshwater and tree resources, which are threatening the very foundations of human society and economic systems (Xu et al., 2023).

The recent scientific development in ecology has given a better understanding of the driving factors of climate changes (Ozturk & Ullah, 2022). Most of these greenhouse gases include carbon dioxide, methane, nitrous oxide and water vapor, and these can definitely be linked to the drastic growth in global warming. By considering the commendable efforts by the global organizations such as the United Nations, the International Union of Conservation of Nature and UN Framework Convention on Climate Change as stipulated in the Kyoto Protocol, it is clear that the current efforts do not suffice towards the effective management of the decline in the world ecosystem (Sathaye et al., 2006). Conversely, there is also an influential opinion that a higher level of environmental sustainability can be achieved due to the considerate implementation of new environmental regulations, laws, and economic means (Wei et al., 2023). This has culminated into detailed analysis on the correlation between ecological integrity and the energy conservation efforts, which realizes that these developments might pose challenges to the free economic development. Consequently, a critical role of policy makers lying in policy formulation is to settle a middle ground where environmental degradation is dealt with alongside sustainable economic development. The first barrier in this endeavor is the identification of reliable and non-polluting energy sources capable of decoupling economic development with the growth in the number of greenhouse emissions (Usman et al., 2021).

The Organization for Economic Cooperation and Development (OECD) is an influential body in shaping global policies on transnational matters, especially in business, trade, education, and climate change (Chang et al., 2023). It is one of the most important goals of the nations that are members of the OECD in the environmental sector to reduce environmental deterioration (END). This target has been accomplished through collaboration on climate change, biodiversity protection, sustainable forest management, and demographic trends. The main policy issue in the alliance is management of END in such a way that the growth of the economy is maintained. This challenge is emphasized by statistics provided by Global Energy Interconnection Development and Cooperation Organization (GEIDCO, 2019), whereby OECD nations on an average portray some of the highest rates of both energy use and associated carbon emissions in the world.

The rest of this investigation follows. In Section 2, we review previous research and propose theories on the correlation between CO_2 emissions and their predictors: RNEF, FNND, FEC, GDP, and DMT. Section 3: Methodology provides the data, nation sample, variables, and mathematical formulation of the FES-based AI model, along with a training flowchart and environmental applications. Section 4: Results and Discussion show and explain intelligent network results on how selected variables affect OECD emissions. Section 5: Conclusion summarizes the research, presents conclusions, limitations, and future directions.

Literature Review

There has been a significant amount of research conducted on the topic of the role that renewable energy finance (RNEF) plays in lowering carbon dioxide emissions and hence reducing environmental deterioration (END). In their early work, Aizawa and Chaofei (2010) conceived of RNEF as a system that would encourage industrialized nations to reduce their emissions by providing preferred loan terms to businesses that have demonstrated exceptional environmental performance. In great part, this effect is supported by empirical research that uses a variety of research approaches. According to M. A. Khan et al. (2022), who applied OLS and fixed effects models to a panel consisting of 26 countries (2011–2019), they discovered that RNEF causes END to decrease by a significant amount. In a similar vein, Q.-J. Wang et al. (2022) made use of a Quantile-on-Quantile Regression (QQR) on the top ten emitters (2008–2019), and Umar and Safi (2023) made use of a Method of Movements Quantile Regression (MMQR) on OECD nations (1990–2019). Both of these studies found that RNEF reduces the degradation of the environment and improves ecological performance. Ma et al. (2023), whose quantile regression research of G-20 countries (2010–2020) reveals improved environmental outcomes via RNEF in developing economies, demonstrate that these findings extend to broader country groupings. They show that these findings are applicable to a wider range of countries. Despite the fact that Zhang et al. (2022), who used a Common Correlated Effects Pooled (CCEP) estimate on 46 countries, also discovered a substantial decrease in END, they solely attribute it to an increase in CO2 emissions. This conclusion is in contradiction to the general agreement that has been established. The weight of evidence from research conducted in established, developing, and underdeveloped environments reveals that RNEF projects have a positive effect on END, particularly through the reduction of carbon emissions. This is the case in the overall context.

H1: RNEF significantly curbs END of OECD by reducing carbon emissions.

The ecological expenditures of the economic activity are often viewed as externalities, which are not considered in the conventional approaches to the measurement of economic growth. It is shown by a substantial amount of empirical literature that there is a negative, causal relationship between the growth in GDP and environmental degradation (END). The model employed by Mujtaba et al. (2022) is a non-linear autoregressive distributed lag (PNARDL) to test the changes in five global regions between 1971 and 2014. Their results showed that economic growth had both the effect of positive and negative influence on CO 2 emissions which all led to the negative effect on END in all regions with exception of North America. This is in agreement with the findings of (Liu et al., 2021), who highlight the significantly harmful influence that economic growth has on emissions in the groups of people with lower-middle incomes. According to (Nasreen et al., 2020), Asia has demonstrated a direct response to this phenomenon, with a change in END of 0.46% occurring for every unit shift in economic growth. This trend is corroborated by the research that was conducted on China by Diao et al. (2009). In their study, the authors establish a connection between the high CO2 emissions associated with this country and the growth-related decline of environmental protection measures. Research on the MENA region offers complex causal evidence: Abdouli and Hammami (2017), using a VAR model of 17 states (1990-2012), found out that economic growth has unidirectional causality on increased emissions and END. Conversely, in their study of 12 countries in MENA, Omri et al. (2015) found a 2-way causal relationship between growth and emissions and a complex, mutually supporting dynamic that constrained the achievement of environmental protection.

H2: The expansion economic growth reduces END of OECD by enhancing carbon emissions.

There is a reduction in the costs of economic transactions as a result of the process of financial development (FNND), which involves increasing the capacities of financial intermediaries and markets and making them more efficient. It would appear that FNND has the capacity to simultaneously assist economic growth and environmental sustainability as a result of the fact that it makes commercial activity easier to carry out. This is in spite of the fact that there is a lack of academic consensus regarding the influence that it has on the environment, with research pointing out in a variety of different directions. It is predicted that FNND has a positive effect, which is that it reduces the amount of carbon dioxide emissions, hence preventing environmental degradation (END). This is according to the findings of one body of research. According to Tao et al. (2023), this can be linked to the larger role that the financial sector plays in encouraging investment toward initiatives that are ecologically friendly. There is a correlation between the two. It is possible to use this as a means of providing an explanation for the phenomenon. This assertion is supported by evaluations that were carried out to the greatest extent that was possible. FNND has been shown to be related with lower emission levels over a longer length of time, as evidenced by study carried out by Khan et al. (2020) countries and by Acheampong et al. (2020) over 83 countries. This has been demonstrated through research. This correlation is also present at the national level, as demonstrated by the findings of the co-integration analysis that Acheampong et al. (2020) conducted for Turkey. It is evident that this association is existent. They came to the realization that there is a negative elasticity of -0.069 between FNND and CO2 emissions, and that this elasticity is accompanied by an adjustment rate of 16.97%. The idea that there is a favorable influence on environmental quality over a longer length of time is supported by this evidence, which demonstrates that this influence is good.

H3: Unstructured FNND enhances END of OECD by increasing carbon emissions.

The worldwide demographic transition (DMT), which is defined by an increasing number of older individuals in the population, has significant repercussions for the socio-economic systems and the environmental sustainability of the current generation as well as the generations who will come after them. Although the effects on healthcare, labor markets, and energy consumption are largely accepted, the relationship with environmental deterioration (END) is a topic that is still being studied in the academic literature. This is despite the fact that the implications are widely acknowledged. On the basis of a substantial amount of research, it has been demonstrated that DMT has a negative impact on the ecosystem. Using two-stage least squares and fixed effects models, , Yuan et al. (2024) conducted an analysis of the data obtained from the Chinese provinces between the years 2003 and 2019. The data under research was collected between 2003 and 2019. Based on the results of their research, it appears that DMT is to blame for the increase in END. This is because DMT is responsible for raising the quantity of

CO_2 emissions that are related with energy usage, particularly in residential settings. Similar to the findings of (Zhou et al., 2023), who suggest that the influence of DMT on emissions is more noticeable in nations that are less developed, they estimate that there was a 3.2% increase in China's energy CO_2 emissions during the transition's inflection point. This is in line with the findings of the previous study. In addition to emerging circumstances, there is evidence that supports the existence of this negative link. Menz and Welsch (2010) conducted research on OECD nations and found that there is a U-shaped link between DMT and environmental quality. This association indicates that END increases with an aging population, which they attribute to age-related health vulnerabilities to pollution. In five of the most populous nations in Africa, Dimnwobi et al. (2021) found that the growth of DMT and the altering age patterns intensify end-of-life concerns. It would appear that the influence is highly dependent on the levels of income. DMT may lead to a decrease in emission intensity in nations with high incomes, according to research carried out by Q. Wang et al. (2022). On the other hand, in countries with lower incomes, it commonly correlates with an increase in CO_2 emissions, reflecting a complex worldwide scenario.

H4: DMT enhances END of OECD by increasing the amount of carbon emissions.

The phrase fossil-based energy consumption (FEC) refers to the entire use of fossil fuels such as coal, oil, and natural gas for a number of reasons, including industrial, transportation, and domestic applications. This utilization can contribute to the overall energy consumption. END, which stands for environmental degradation, is typically associated with this particular sort of energy usage. Numerous pieces of evidence establish a connection between the growth of fossil fuel energy centers (FEC) and the escalation of carbon dioxide emissions and the deterioration of the environment. A distinction is made in the research between the consequences of using renewable energy sources and those of using energy that is derived from fossil fuels sources. According to Adams et al. (2020), who applied an IV-GMM methodology to 19 countries in Sub-Saharan Africa between the years 1980 and 2011, they found that transportation-related FEC directly increases CO_2 emissions, which in turn intensifies END. This was discovered by applying the methodology to the countries. (Yusuf, 2023), who conducted an analysis of Nigeria using an ARDL model with structural breakdowns (1980–2020), provides additional evidence that strengthens the connection between these two components. The results of his research demonstrate how a major reliance on fossil fuels is a contributing factor to the destruction of the ecosystem. In a similar line, research carried out by Khan et al. (2022) on OECD nations (1990–2015) suggests that the consumption of non-renewable energy is the primary factor that accounts for end-of-life (END) in developed economies. Because of this discovery, a number of member states are compelled to work toward achieving energy independence and to reinforce their economic institutions to protect themselves from vulnerabilities of this kind.

H5: The FEC enhances intensity of END of OECD by raising CO_2 emissions.

Empirical Data and Research Methodology

Empirical Data

This research utilizes quarterly data spanning from the first quarter of 2000 to the fourth quarter of 2023 for OECD member countries to analyze the influence of renewable energy finance (RNEF) on environmental degradation (END). The primary variables are defined in the following manner: END is represented by CO_2 emissions, while RNEF is indicated by financial investment flows into renewable energy sources. Control variables encompass financial development (FNND), quantified as the broad money supply relative to GDP; fossil energy consumption (FEC), articulated as primary energy consumption per capita (kWh/person); economic growth, indicated by GDP per capita (constant 2015 US$); and demographic transition (DMT), determined by the population proportion aged 65 and older. The majority of the data for CO_2 emissions, RNEF, and FEC comes from databases maintained by the OECD. On the other hand, the data for the other variables comes from the World Development Indicators (WDI) program maintained by the World Bank. Through the utilization of the quadratic match-sum interpolation method, annual data are transformed into quarterly frequency in order to achieve a higher level of analytical granularity. Research that was done in the past has shown that this method is effective (Kirikkaleli & Ali, 2023). For the purpose of conducting a more in-depth investigation of the impact that RNEF has on the dynamics of END, this transformation makes it possible to undertake the analysis. The definitions of all variables, as well as the measurements of those variables, are presented in a condensed form in Table 1.

Table 1

Variable list and explanation

Variable list	Symbolization	Variable details	Source of data
Dependent Variable			
Environmental degradation	CO2 emission	CO_2 Emission (kt)	OECD database
Independent variable			
Renewable energy financing	RNEF	Financial investment in multiple renewable energy sources (USD Mn)	OECD database
Control variables			
Financial developments	FNND	Broad money (% of GDP)	WDI
Fuel-based energy consumption	FEC	Primary energy consumption per capita (kWh/person)	OECD database
Economic growth	GDP	GDP per capita (constant 2015 US$)	WDI database
Demographic transition	DMT	The percentage of individuals aged 65 years and older in relation to the overall population.	WDI database

FES-Based AI Modelling

The offered methodology makes use of an artificial intelligence model that is supervised and based on FES in order to carry out multivariate regression analysis on panel data. In this supervised method, the segmentation of the dataset into input-output pairs is an essential step that requires careful attention. In a sample size of N, the $n-th$ pair comprises an input vector $x(n)$ and its corresponding desired output $d(n)$, where $x(n) = [x_1(n) \quad x_2(n) \cdots x_n(n)]^T$. The model consists of L computational layers, excluding the input layer, which is indexed as $l = 0$. Each hidden layer comprises neurons. The fundamental learning process entails the iterative modification of synaptic weights. The weight linking neuron i in the previous layer to neuron j in layer l at training iteration k is denoted as $w_{l,j,i}^{[k]}$. The activation of the $j-th$ neuron in layer l for the input x(n) is represented by the output $y_{l,j}(n)$, as shown in Figure 1. With the first element being a bias unit and the succeeding elements being neuron activations computed using a threshold function T, the output vector of the layer is denoted by the expression $y_l(n) = [\, y_{l,0}(n) \quad y_{l,1}(n) \cdots y_{l,m_l}(n)\,]^T$ raised to the power of T. The activity of a particular neuron may therefore be summarized as follows:

$$v_{l,j}(n) = \sum_{i=0}^{m_{l-1}} w_{l,j,i}\, y_{l-1,i}(n) \qquad (1)$$

Take into consideration the training example $(x(1), y_L(1))$ where $x(1)$ represents an input feature vector with dimensions of $m_0 \times 1$ and $y_L(1)$ represents the goal output of the final layer L consisting of dimensions of 1×1. With the addition of a bias unit, which is specified as $y_{0,0}(1) = 1$, the input layer is completed. The activation vector for the first hidden layer $(l = 1)$ is formulated as follows, with the iteration index k being omitted for the sake of clarity:

$$y_{l,0}(1) = \boldsymbol{\sigma}\Big((\boldsymbol{W}_l\, x(1))\big(y_{1,0}(1)\big) \;\; \textit{is added to} \;\; (y_l(1))\Big) \qquad (2)$$

Figure 1

Architecture of FES-based AI model (L = 6)

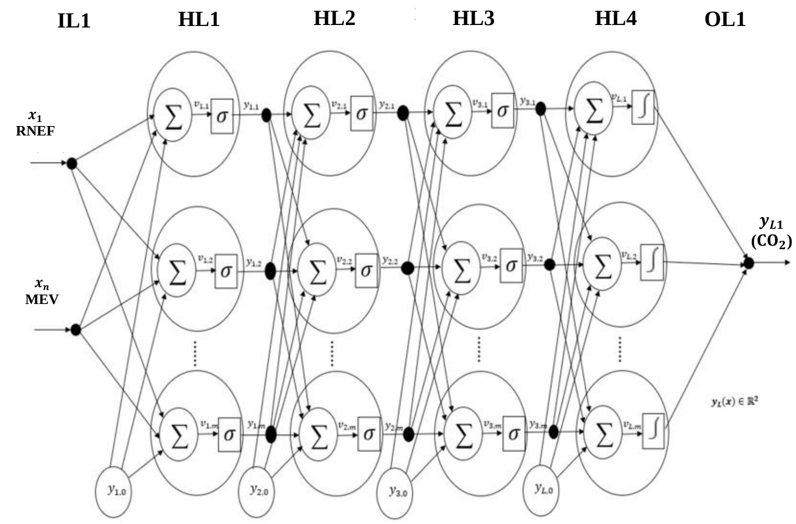


Figure 1 illustrates the network design, which has an input layer, three hidden layers, and an output layer, each containing a configurable number of neurons. A tapering design minimizes complexity by reducing the number of neurons in subsequent hidden layers (see to appendix for overview), however this quantity remains adjustable. Each neuron gets input from a bias unit to represent constant offsets. Forward propagation is executed in a vectorial manner. For layer l, with weight matrix w_l^k of dimensions $m_l \times (m_l + 1)$ and activation vector $v_l(n)$ of dimensions $m_l \times 1$ the procedure starts by augmenting the activation vector $v_{l,0}(n)$ from the preceding layer with a bias element $v_l(n)$. In order to facilitate the propagation of $x(1)$ through the activation function $\boldsymbol{\sigma}$, the matrix $\boldsymbol{W_l}$ offers assistance. The $y_{1,0}(1)$ is a bias term that is applied to the output of the first hidden layer, which is denoted by $y_l(1)$. When l is equal to 1, 2, 3, etc., the forward pass that connects layers l and $l+1$ is described by the following relationship:

$$y_{l+1}(1) = \boldsymbol{\sigma}\Big((\boldsymbol{W}_l y_l(1)) \big(y_{l+1,0}(1)\big) \textit{ is added to } \big(y_{l+}\ \big) \tag{3}$$

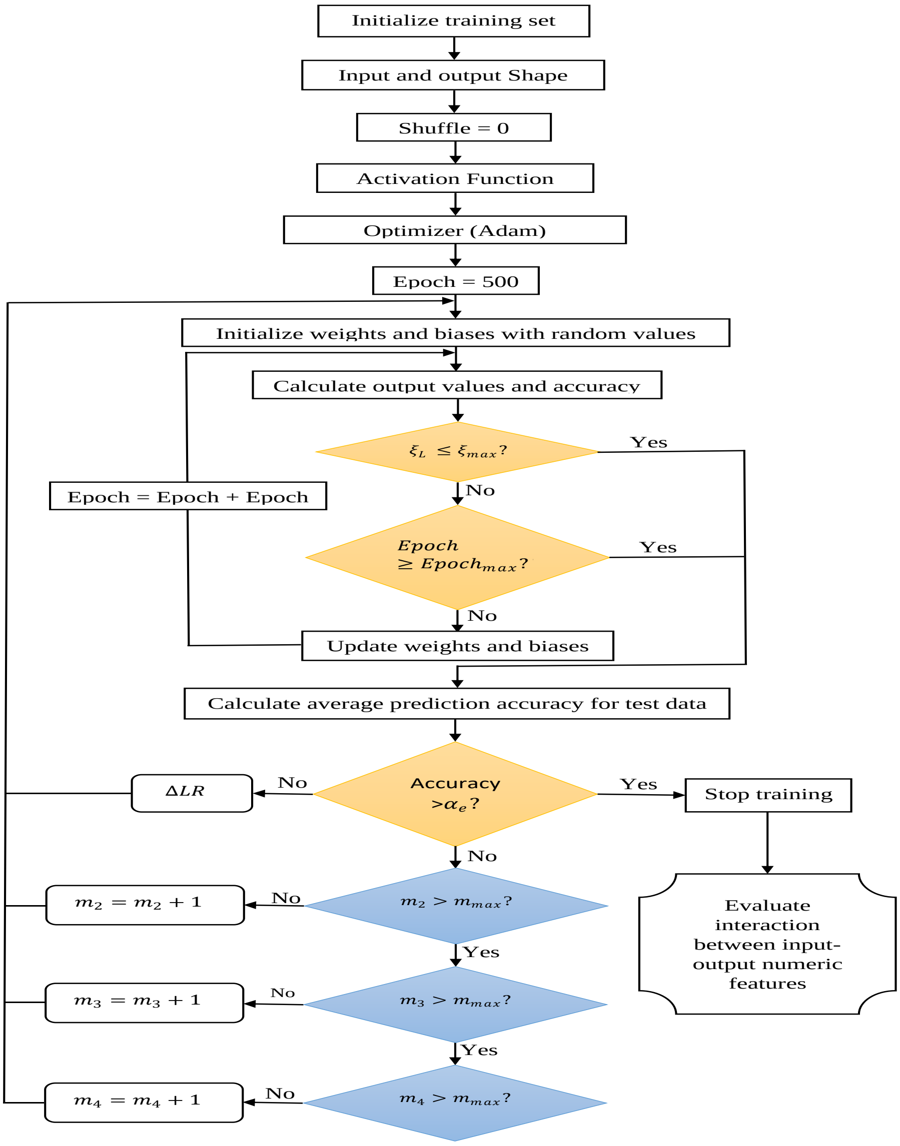
The bias parameter for the $l+1-th$ layer in this case is $y_{l+1,0}(1)$. In order to make the model more effective, this parameter is changed often. At last, the output of the network is generated by the $L-th$ layer, which is represented as:

$$y_L(1) = \int\left(\sum_{j=1}^{m_L} W_L\, y_L(1) + (\,y_{L,0}(1)\,) \textit{ is added to } y_L(1) \right) \tag{5}$$

In the last layer, the output $y_L(1)$ is made up of the outputs of the m_L neurons in addition to an integrated bias term, which is denoted by the expression $y_{L,0}(1)$ Figure 2 illustrates the process of backpropagation, which is a mechanism that refines the synaptic weights and bias values across the design. This procedure is used to maximize the performance of the network.

Figure 2

Flowchart of training process of FES-based AI model



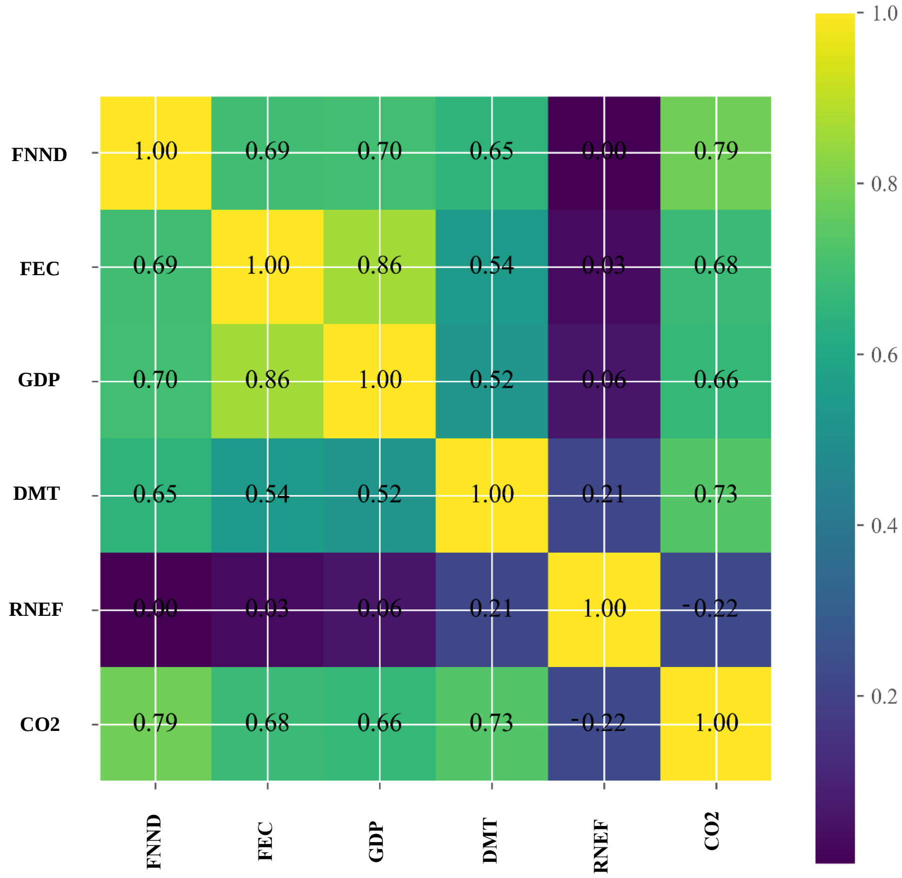
A flowchart of the training pipeline is presented in Figure 2. This pipeline is comprised of five essential steps, which are as follows: data collection, preprocessing, exploration/visualization, model creation, and estimating procedures. The preparation of data is very important for the proper use of model initialization. While designing the architecture, a typical heuristic (Duan, 2019) is taken into consideration. According to this heuristic, the total number of neurons in hidden layers must be greater than half of the input count as $\sum_{l=1}^{L-1} n_l > x_n/2$. The process of optimization comprises the tweaking of weights and biases, and training is only completed when the error of the model goes below a target that is desired. Backpropagation is used in conjunction with extra training epochs in the event that this aim is not achieved.

Experimental Results

The empirical findings are presented in three primary formats to ensure that they are both clear and comprehensive. These formats include: (i) a correlation matrix that shows how key variables are related to each other; (ii) performance metrics that come from training and testing the FES-based AI model and look at how variables interact; and (iii) three-dimensional visualizations that make the results easier to understand and see.

Figure 3

Empirical correlation matrix of significant variables of the study



As shown in Figure 3, the correlation matrix provides an overview of the correlations that exist between the major variables. According to the findings, the coefficients for FNND, FEC, GDP, and DMT are 0.79, 0.68, 0.66, and 0.73, respectively, indicating that these variables have a positive and substantial statistical relationship with CO_2 emissions. It has also been shown that there are positive intercorrelations between RNEF, FNND, FEC, GDP, and DMT. Among these, there is a significant connection between FEC and GDP measuring 0.86. On the other hand, RNEF has a negative correlation with CO_2 emissions (-0.22). The notion that RNEF improves environmental quality by lowering carbon emission is supported by this trend, which is consistent with the scientific literature that is currently available.

Fes-Based Ai Model Findings

As shown in Figure 1, the architecture of the FES-based artificial intelligence model is composed of five levels that are tightly coupled to one another. These layers include one input layer, three hidden layers, and one output layer. The optimization of the model was accomplished through the use of backpropagation techniques, and the whole workflow of the procedure is represented in Figure 2. According to the information presented in Table 2, the network is completely linked, and the parameter summary substantiates that it is in a trained state. A visual representation of the learning trend can be found in Figure 4, which further displays the training and validation loss curves. Table 4, which may be found in Appendix A, contains a list of further structural features of the particular model. The implementation of numerous activation functions, in addition to the division of data into training and testing sets, was also carried out.

Figure 4

Loss of FES-based AI model

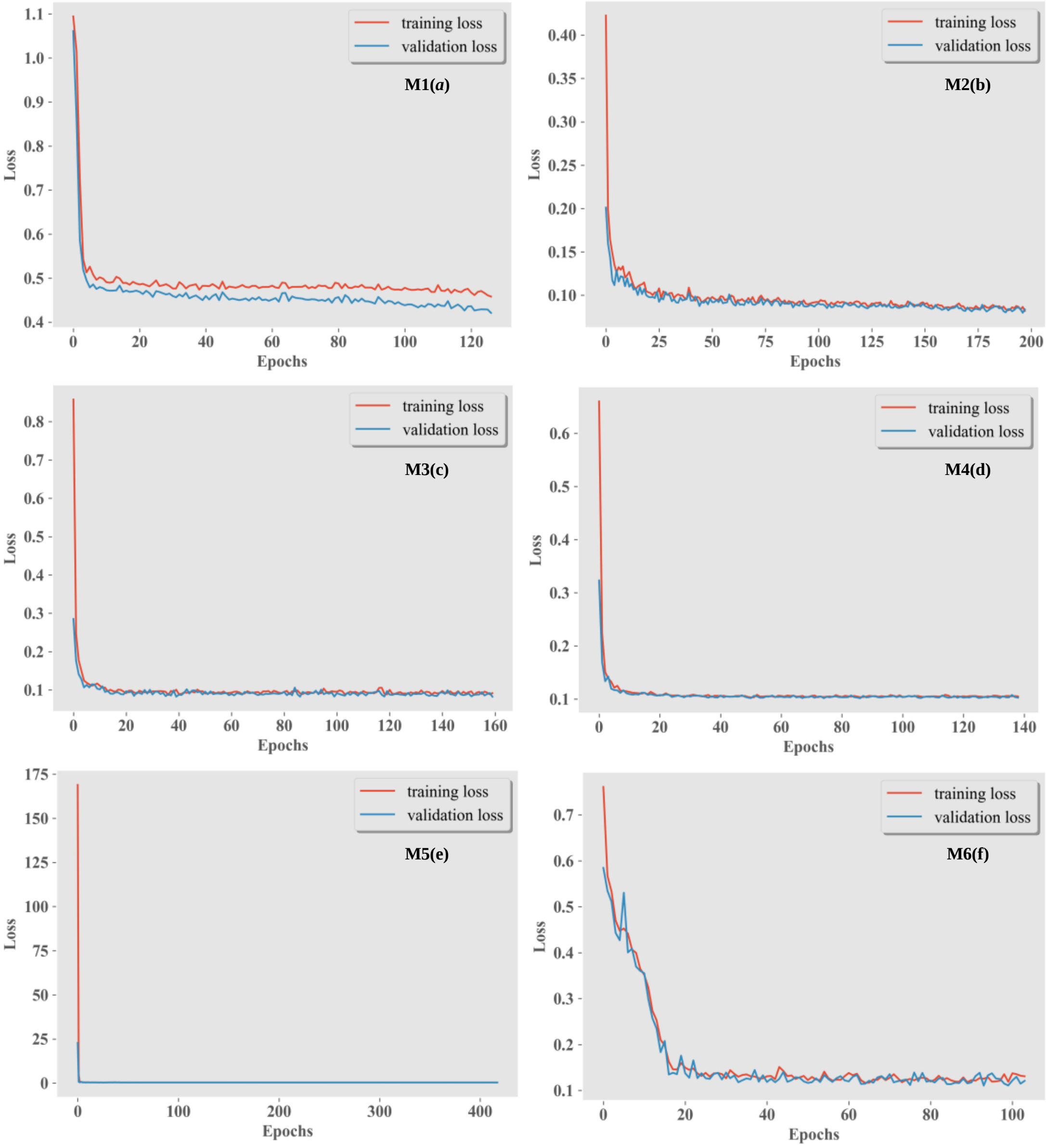


Figure 4 consists of six subplots depicting the training and validation loss curves of the different model versions given. The y-axis represents the loss value associated with the individual epochs, while the x-axis indicates the number of epochs. It is often noted that the training and validation losses diminish with an increase in the number of epochs across all graphs, signifying effective learning. Subplot M1(a), representing the model with a sigmoid activation function, exhibits convergence after around 120 epochs. Subplot M2(b), representing the model employing a ReLU activation function, exhibits the most optimal reduction in loss among the variants. This is demonstrated by the fact that its loss curves are uniformly smooth and descending in nature. All of the subplots, beginning with M1(a) and ending with M6(f), each show a different model that makes use of a different activation function. This makes it possible to do a comparative diagnostic in order to determine whether function aligns with the final model estimation in the most consistent manner.

Table 2

Summary of FES-based AI model

No. of dense layer	No. of neurons each layer	No. of params
1	512	3072
2	256	131328
3	128	32896
4	64	8256
5	32	2080
6	1	33

Note: Total params :177665, trainable params: 177665, nontrainable params: 0

The architecture of the proposed paradigm is broken down into its component parts and may be found in Table 2. One layer is designated for input, three tiers are concealed from view, and one tier is designated for output. The architecture is composed of five stages. A tapering design is utilized in order to lessen the level of complexity that the model possesses. Through a reduction in the total number of neurons, this architecture brings in a reduction in the number of neurons that are successful in buried layers. As a result of the fact that there are no non-trainable parameters, which is equal to zero, the summary offers evidence that the model can be trained in its entirety.

Table 3

Output of FES-based AI model on testing dataset

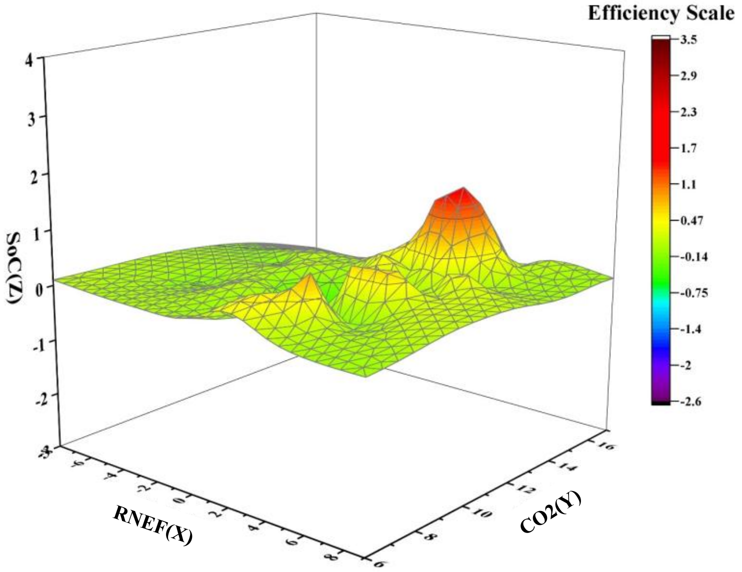
Model	Function	Intercept	Coefficient	R^2	MSE
M1	Sigmoid	0.4284	0.4896	0.5781	0.3489
M2	ReLU	0.1063	0.7429	0.8925	0.0872
M3	Tanh	0.1208	0.7951	0.8786	0.0995
M4	SoftMax	0.1329	0.6658	0.8679	0.1093
M5	Linear	0.3952	0.5124	0.6058	0.3327
M6	Miscellaneous	0.1541	0.0952	0.8474	0.1271

The results of six alternative FES-based artificial intelligence models, each of which utilized a different activation function, are presented in Table 3. These models were evaluated using a separate testing dataset. The performance of each model is assessed through four primary metrics: the Intercept, which reflects the baseline level of CO_2 emissions independent of input variables; the Coefficient, which quantifies the sensitivity of CO_2 emissions to a one-unit change in the composite input variable (encompassing RNEF, FNND, FEC, GDP, and DMT); R^2, which denotes the proportion of variance in emissions accounted for by the model; and MSE, which indicates the average squared prediction error or loss. The investigation shows that models work better in a defined order. Model M2 performs better than other models when the ReLU activation function is used. The model has an R2 value of 0.8925, which means that it explains about 89.25% of the changes in CO2 emissions. This means that the model is quite good at explaining things. It also has the lowest mean squared error (MSE = 0.0872), which means that it has better anticipated accuracy and less loss. According to the coefficient of 0.7429 in the model, there is a high positive correlation between the two variables. This indicates that an increase of one unit in the composite input variable corresponds to an increase of 0.74 units in emissions. In addition, the low interception of 0.1063 suggests that the external baseline effect is not particularly significant.

Despite the fact that other non-linear activation functions demonstrate impressive performance, the ReLU model is able to outperform them by a somewhat greater margin. With a coefficient of 0.7951 and a significant R2 value of 0.8786, Model M3 (Tanh) is the one that features the highest coefficient performance. It has been demonstrated that the R2 value for Model M4 (SoftMax) is 0.8679. The fact that both models have low error rates, with mean squared errors of 0.0995 and 0.1093, respectively, demonstrates that they are effective in reflecting the data relationships that lie beneath the surface. There are substantial restrictions that are demonstrated by the models that use functions that are either less appropriate or simpler. Model M1 (Sigmoid) and Model M5 (Linear) both have significantly larger prediction errors, with mean squared errors of 0.3489 and 0.3327, respectively. These models only explain for 57.81% and 60.58% of the variation, respectively, and provide significantly higher levels of prediction error. Having interceptive values that are higher than average suggests that a bigger proportion of the emissions output can be attributed to external factors that are not accounted for by the inputs. In spite of the fact that it has a relatively low coefficient of 0.0952, which indicates a weak marginal effect, Model M6 (Miscellaneous) continues to retain a high R2 value of 0.8474. This shows that it has an uncommon profile. This indicates that the model's structure or the various functions may be accounting for variance via the intercept or other intricate, non-linear interactions that are not explicitly represented in the marginal coefficient. The findings demonstrate a robust and explicable correlation between the chosen economic and demographic variables and CO_2 emissions in OECD nations. The metrics of the ReLU-based model (M2) confirm its selection as the most reliable and accurate configuration for drawing conclusions and for subsequent graphical analysis within the study.

Figure 5

3D mappinge interaction between RNEF and CO_2 with FES-based AI model



By charting the slope of variable coefficients in a three-dimensional space, Figure 5 provides a visual representation of the link that exists between RNEF and CO2 emissions in OECD participating nations. Both the independent variable (RNEF) and the dependent variable (CO2 emissions) are mapped to the X and Y axes, respectively, while the Z axis displays the projected coefficient slope that was produced from the intelligent network. Utilizing a color gradient scale gives one the ability to ascertain the level of interaction that is taking place. The story suggests that there are two distinct governments in existence. The lower-to-middle region that is predominant exhibits a slight incline in the opposite direction, which is represented by colors that are light green. So, this shows that a higher RNEF is generally linked to lower CO2 emissions, which helps slow down the decline of the environment (END). On the other hand, one of the highest areas is a smaller one with a steeply positive slope that is distinguished by intense red and yellow colors. This shows that RNEF and emissions traveled together for a while. This strange positive link could be the result of outside events, such the spike in transportation and industrial activity that happened following the outbreak because more people wanted to travel and buy basic goods. This surge happened even when the RNEF was growing, which is a trend that current research supports (Ahmed Memon et al., 2024; Kherazi et al., 2024). This spike in emissions was just brief. But overall, the graphs show that RNEF has a big effect on lowering CO2 emissions and END intensity in all of the OECD member nations. This is true for everyone.

Figure 6

3D mapping interaction between GDP and CO_2 with FES-based AI model

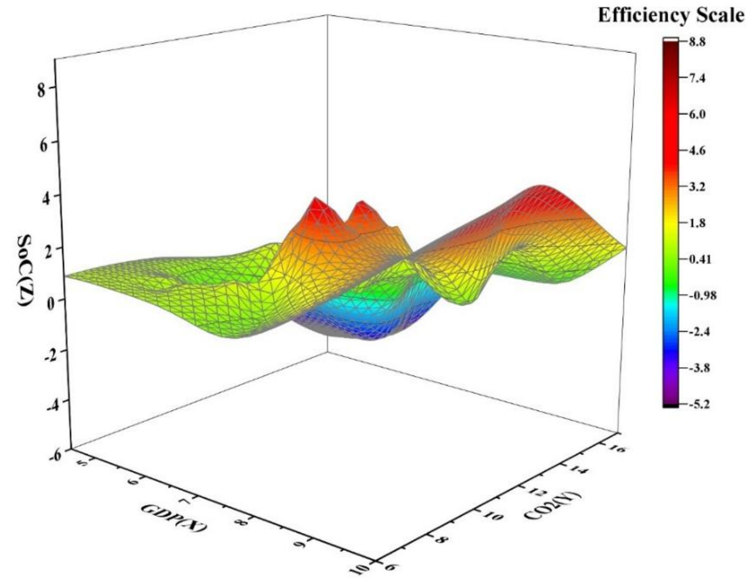


Figure 6 is a graphical representation of a study that reveals a significant positive association between the gross domestic product and the emissions of carbon dioxide. There is a continuous range of green, yellow, and red colors that are used to illustrate this correlation. According to this trend, which is corroborated by the positive slope of the coefficient, economic expansion in OECD nations contributes to the worsening of environmental degradation by increasing the amount of carbon emissions from those countries. Furthermore, despite the fact that this anomaly does not change the fundamentally positive trend that was seen across the dataset, a dark blue patch that is isolated signals a temporary negative spike.

Figure 7

3D mapping interaction between FNND and CO_2 with FES-based AI model

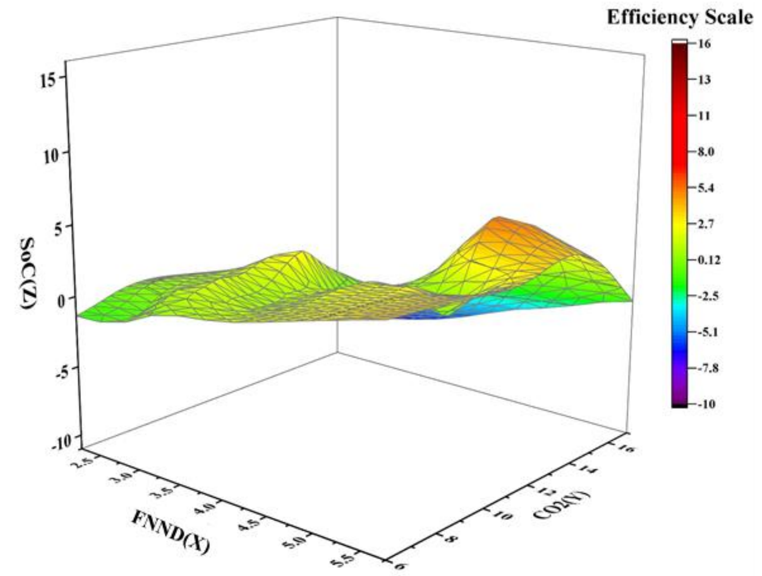
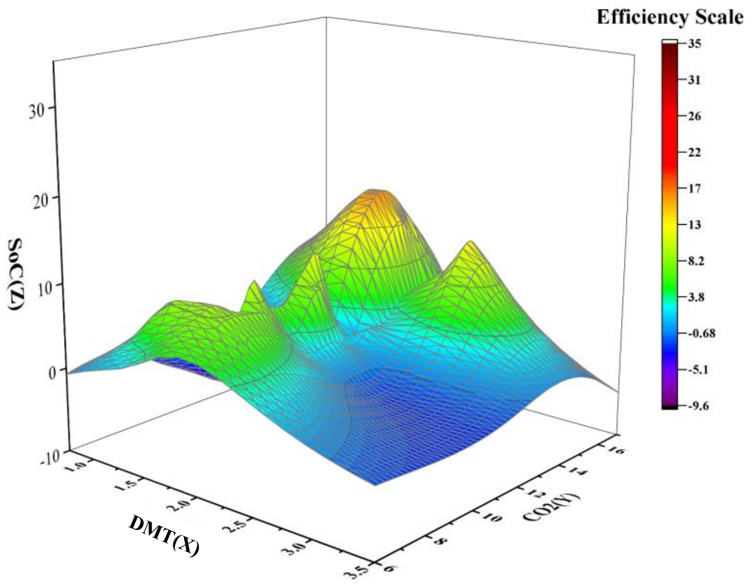


Figure 7 is a visual representation of the coefficient slopes that were obtained from the intelligent network model in order to illustrate the interaction between FNND and END reduction and CO2 emission rate. The three-dimensional plot of FNND vs CO2 emissions reveals a split pattern. The variables are plotted on the X and Y axes, and the coefficient slope is plotted on the Z axis. Particularly light-green regions provide evidence that, in the majority of the observed ranges, financial development in OECD nations corresponds with decreases in emissions, which lends credence to the mitigation of end-of-life emissions. On the other hand, there is a unique upper zone that is colored yellow, and it represents an opposing regime in which the development of FNND is connected to growing emissions and increased environmental deterioration.

Figure 8

3D mapping interaction between DMT and CO_2 with FES-based AI model



A positive correlation between demographic transition (DMT) and CO2 emissions is seen in Figure 8. This is demonstrated by the predominant green and yellow color gradient that runs throughout the plot. This link is supported by the fact that the coefficient has a positive slope, which indicates that the aging of populations in OECD nations is a contributing factor to rising emissions and increased environmental deterioration (END) intensity. Despite the fact that a single downward spike, which is denoted by the color blue, constitutes a slight divergence, the general upward trend is not affected either.

Figure 9

3D mapping interaction between FEC and CO_2 with FES-based AI model

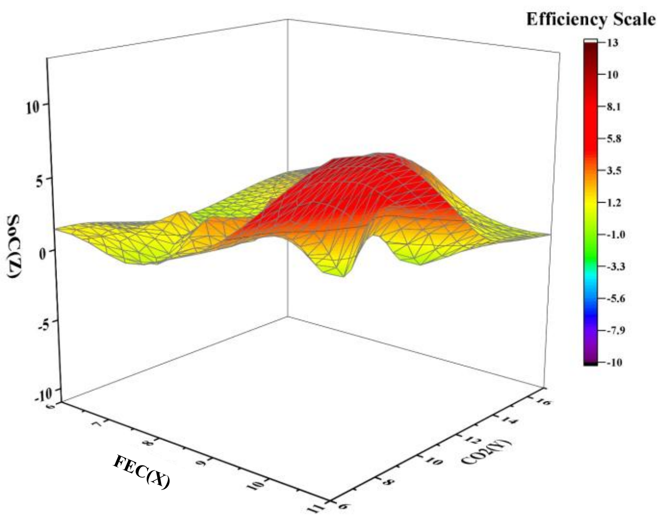
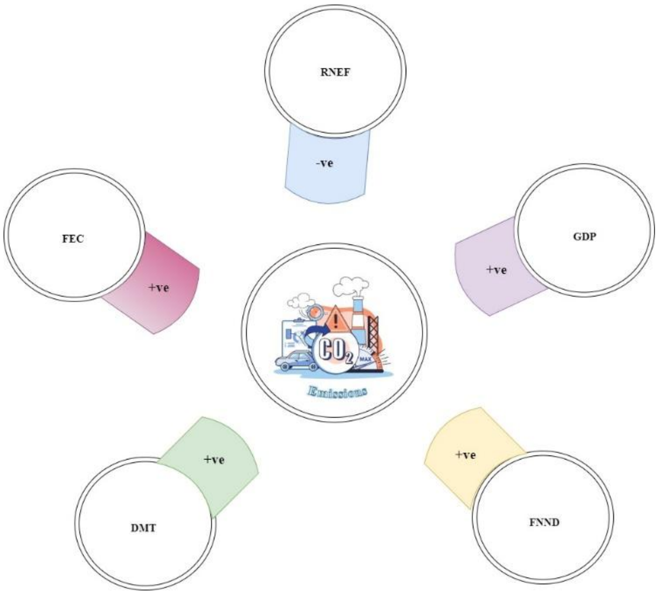


Figure 9 demonstrates a pronounced positive relationship between fossil energy consumption (FEC) and CO_2 emissions, as visualized by the dominant yellow and red coloration across the plot. The fact that the slope of the associated positive coefficient is positive demonstrates that an increased FEC contributes to an intensification of environmental deterioration (END) in OECD countries via increasing emissions. In conclusion, the integrated findings from the FES-based AI modeling and graphical analysis concluded that renewable energy finance (RNEF) helps to protect the environment by reducing the amount of carbon dioxide emissions. On the other hand, financial development (FNND), use of fossil fuels (FEC), economic growth (GDP), and demographic transition (DMT) are all connected with increased end-of-life (END) due to the favorable impact that they have on carbon emissions.

Figure 10

Summary of the findings and predetermined hypotheses achievements



Considering the established assumptions regarding the influence of each variable on CO2 emissions and environmental degradation (END), the summary that is presented in Figure 10 provides support for those variables. There is a significant inverse association between the financing of renewable energy and the reduction of emissions, which suggests that more investment in renewables leads to a reduction in emissions and helps alleviate END, which supports the achievement of H1.1. On the other hand, fossil-based energy consumption (FEC), financial development (FNND), economic growth (GDP), and demographic transition (DMT) all show a positive correlation with CO2 emissions. This means that these traits help raise END in OECD countries, which also help H2, H3, H4, and H5 be reached. RNEF protects the quality of the environment, while FEC, FNND, GDP, and DMT all make carbon emissions and ecological damage worse. The data collectively corroborates the study's expectations, demonstrating a clear differentiation between the two scenarios.

Conclusion

This study employed a model of artificial intelligence grounded in FES to examine the interrelations among renewable energy financing (RNEF), financial development (FNND), fossil-based energy consumption (FEC), gross domestic product (GDP), demographic transition (DMT), and environmental degradation (END) within OECD member countries. The primary indicator employed in this scenario was carbon dioxide emissions. The intelligent network analysis has helped us find two important things. First, raising RNEF effectively lowers carbon emissions, which helps lessen the effects of END. A rise in emissions, which in turn makes END worse, is caused by an increase in FNND, FEC, GDP, and DMT, all of which contribute to an increase in emissions. Moreover, the model indicates strong conditional interactions: the environmental consequences of FEC, GDP, and DMT are moderated by the amount of FNND, and the relationship between END and emissions is itself conditioned by the extent of RNEF. These interactions are evidenced by the fact that the model reveals significant conditional interactions. It is clear from the model that these conditional interactions are significant in the grand scheme of things. RNEF and FNND are in a position to become significant drivers that have the power to influence the effect that economic and demographic pressures have on the quality of the environment as a result of their actions. The fresh contribution that these insights into conditional dependencies provide distinguishes this research from the existing literature that has been done on the subject. Therefore, the significance of this discovery is elevated, and the scope of the discussion around climate change is broadened as a consequence.

Policies and research are both impacted by the findings. The policymakers should implement financial instruments in a strategic manner in order to channel capital towards renewable energy development finance (RNEF), green securities, and concessional loans; streamline regulatory certification for low-carbon and green industries while simultaneously integrating environmental priorities into governance structures; and simplify the issuance of green financial instruments and targeted green financial non-development initiatives in developing economies. The results of this study demonstrate that conventional methods of analysis are frequently inadequate for the high-volatile, large-scale datasets that are associated with energy and environmental investigations. Researchers and analysts are provided with a powerful instrument for evaluating complex relationships between energy production, consumption, and environmental sustainability when they have access to a complete, network-based FES-based artificial intelligence framework. This study provides useful insights; yet, it is limited by limits that reveal prospective pathways for further research. Additionally, the study has several drawbacks. Only nine nations from the OECD were included in the sample; a more comprehensive dataset from the OECD would make it easier to draw more definitive conclusions. The analysis focused on emerging economies. A comparative analysis utilizing data from both developed and developing countries, examined through a hybrid FES-based AI model, may provide enhanced understanding of the RNEF-END nexus and more effective policy solutions for energy sustainability.

Funding

This study is not supported by founding.

Declaration About Generating Ai

Author declare that she did not used any AI tool for analysis and write up to accomplish this research.

Credit Authorship Contribution Statement

Author (Rabia Akram) is a sole contributor in all sections of this research.

Competing interests

The authors declare conflict of interest.

Acknowledgements

We thank the editors and anonymous reviewers for their insightful remarks, which greatly improved our article. Author is responsible for lingering mistakes.

References

Abdouli, M., & Hammami, S. (2017). Investigating the causality links between environmental quality, foreign direct investment and economic growth in MENA countries. *International Business Review, 26*(2), 264–278. https://doi.org/10.1016/j.ibusrev.2016.07.004
Google Scholar Worldcat Fulltext

Acheampong, A. O., Amponsah, M., & Boateng, E. (2020). Does financial development mitigate carbon emissions? Evidence from heterogeneous financial economies. *Energy Economics, 88*, 104768. https://doi.org/10.1016/j.eneco.2020.104768
Google Scholar Worldcat Fulltext

Adams, S., Boateng, E., & Acheampong, A. O. (2020). Transport energy consumption and environmental quality: Does urbanization matter? *Science of The Total Environment, 744*, 140617. https://doi.org/10.1016/j.scitotenv.2020.140617
Google Scholar Worldcat Fulltext

Ahmed Memon, B., Aslam, F., Naveed, H. M., Ferreira, P., & Ganiev, O. (2024). Influence of the Russia–Ukraine War and COVID-19 pandemic on the efficiency and herding behavior of stock markets: Evidence from G20 nations. *Economies, 12*(5).
Google Scholar Worldcat Fulltext

Aizawa, M., & Chaofei, Y. (2010). Green credit, green stimulus, green revolution? China's mobilization of banks for environmental cleanup. *The Journal of Environment & Development, 19*(2), 119–144. https://doi.org/10.1177/1070496510371192
Google Scholar Worldcat Fulltext

Chang, S., Chen, B., & Song, Y. (2023). Militarization, renewable energy utilization, and ecological footprints: Evidence from RCEP economies. *Journal of Cleaner Production, 391*, 136298. https://doi.org/10.1016/j.jclepro.2023.136298
Google Scholar Worldcat Fulltext

Diao, X. D., Zeng, S. X., Tam, C. M., & Tam, V. W. Y. (2009). EKC analysis for studying economic growth and environmental quality: A case study in China. *Journal of Cleaner Production, 17*(5), 541–548. https://doi.org/10.1016/j.jclepro.2008.09.007
Google Scholar Worldcat Fulltext

Dimnwobi, S. K., Ekesiobi, C., Madichie, C. V., & Asongu, S. A. (2021). Population dynamics and environmental quality in Africa. *Science of The Total Environment, 797*, 149172. https://doi.org/10.1016/j.scitotenv.2021.149172
Google Scholar Worldcat Fulltext

Du, G. (2023). Nexus between green finance, renewable energy, and carbon intensity in selected Asian countries. *Journal of Cleaner Production, 405*, 136822. https://doi.org/10.1016/j.jclepro.2023.136822
Google Scholar Worldcat Fulltext

Duan, J. (2019). Financial system modeling using deep neural networks (DNNs) for effective risk assessment and prediction. *Journal of the Franklin Institute, 356*(8), 4716–4731. https://doi.org/10.1016/j.jfranklin.2019.01.046
Google Scholar Worldcat Fulltext

Khan, M. A., Riaz, H., Ahmed, M., & Saeed, A. (2022). Does green finance really deliver what is expected? An empirical perspective. *Borsa Istanbul Review, 22*(3), 586–593. https://doi.org/10.1016/j.bir.2021.07.006
Google Scholar Worldcat Fulltext

Khan, M. I., Teng, J. Z., & Khan, M. K. (2020). The impact of macroeconomic and financial development on carbon dioxide emissions in Pakistan: Evidence with a novel dynamic simulated ARDL approach. *Environmental Science and Pollution Research, 27*(31), 39560–39571. https://doi.org/10.1007/s11356-020-09304-z
Google Scholar Worldcat Fulltext

Khan, Z., Zakari, A., Ahmad, M., Irfan, M., & Hou, F. (2022). Linking energy transitions, energy consumption, and environmental sustainability in OECD countries. *Gondwana Research, 103*, 445–457. https://doi.org/10.1016/j.gr.2021.10.026
Google Scholar Worldcat Fulltext

Kherazi, F. Z., Sun, D., Sohu, J. M., Junejo, I., Naveed, H. M., Khan, A., & Shaikh, S. N. (2024). The role of environmental knowledge, policies and regulations toward water resource management: A mediated-moderation of attitudes, perception, and sustainable consumption patterns. *Sustainable Development.* https://doi.org/10.1002/sd.2991
Google Scholar Worldcat Fulltext

Kirikkaleli, D., & Ali, K. (2023). Patents on environmental technologies and environmental degradation in a Scandinavian country: Evidence from novel Fourier-based estimators. *Geological Journal, 58*(7), 2595–2609. https://doi.org/10.1002/gj.4722
Google Scholar Worldcat Fulltext

Liu, X., Li, X., Shi, H., Yan, Y., & Wen, X. (2021). Effect of economic growth on environmental quality: Evidence from tropical countries with different income levels. *Science of The Total Environment, 774*, 145180. https://doi.org/10.1016/j.scitotenv.2021.145180
Google Scholar Worldcat Fulltext

Ma, M., Zhu, X., Liu, M., & Huang, X. (2023). Combining the role of green finance and environmental sustainability on green economic growth: Evidence from G-20 economies. *Renewable Energy, 207*, 128–136. https://doi.org/10.1016/j.renene.2023.02.046
Google Scholar Worldcat Fulltext

Menz, T., & Welsch, H. (2010). Population aging and environmental preferences in OECD countries: The case of air pollution. *Ecological Economics, 69*(12),

2582–2589. https://doi.org/10.1016/j.ecolecon.2010.08.002
Google Scholar Worldcat Fulltext

Mujtaba, A., Jena, P. K., Mishra, B. R., Kyophilavong, P., Hammoudeh, S., Roubaud, D., & Dehury, T. (2022). Do economic growth, energy consumption and population damage the environmental quality? Evidence from five regions using the nonlinear ARDL approach. *Environmental Challenges, 8*, 100554. https://doi.org/10.1016/j.envc.2022.100554
Google Scholar Worldcat Fulltext

Mundaca, G., Strand, J., & Young, I. R. (2021). Carbon pricing of international transport fuels: Impacts on carbon emissions and trade activity. *Journal of Environmental Economics and Management, 110*, 102517. https://doi.org/10.1016/j.jeem.2021.102517
Google Scholar Worldcat Fulltext

Nasreen, S., Mbarek, M. B., & Atiq-ur-Rehman, M. (2020). Long-run causal relationship between economic growth, transport energy consumption and environmental quality in Asian countries: Evidence from heterogeneous panel methods. *Energy, 192*, 116628. https://doi.org/10.1016/j.energy.2019.116628
Google Scholar Worldcat Fulltext

Omri, A., Daly, S., Rault, C., & Chaibi, A. (2015). Financial development, environmental quality, trade and economic growth: What causes what in MENA countries. *Energy Economics, 48*, 242–252. https://doi.org/10.1016/j.eneco.2015.01.008
Google Scholar Worldcat Fulltext

Ozturk, I., & Ullah, S. (2022). Does digital financial inclusion matter for economic growth and environmental sustainability in OBRI economies? An empirical analysis. *Resources, Conservation and Recycling, 185*, 106489. https://doi.org/10.1016/j.resconrec.2022.106489
Google Scholar Worldcat Fulltext

Sadorsky, P. (2011). Financial development and energy consumption in Central and Eastern European frontier economies. *Energy Policy, 39*(2), 999–1006. https://doi.org/10.1016/j.enpol.2010.11.034
Google Scholar Worldcat Fulltext

Sathaye, J., Shukla, P. R., & Ravindranath, N. H. (2006). Climate change, sustainable development and India: Global and national concerns. *Current Science, 90*(3), 314–325. https://www.jstor.org/stable/24091865
Google Scholar Worldcat Fulltext

Tao, M., Sheng, M. S., & Wen, L. (2023). How does financial development influence carbon emission intensity in the OECD countries: Some insights from the information and communication technology perspective. *Journal of Environmental Management, 335*, 117553. https://doi.org/10.1016/j.jenvman.2023.117553
Google Scholar Worldcat Fulltext

Umar, M., & Safi, A. (2023). Do green finance and innovation matter for environmental protection? A case of OECD economies. *Energy Economics, 119*, 106560. https://doi.org/10.1016/j.eneco.2023.106560
Google Scholar Worldcat Fulltext

Usman, A., Ozturk, I., Hassan, A., Maria Zafar, S., & Ullah, S. (2021). The effect of ICT on energy consumption and economic growth in South Asian economies: An empirical analysis. *Telematics and Informatics, 58*, 101537. https://doi.org/10.1016/j.tele.2020.101537
Google Scholar Worldcat Fulltext

Wang, Q., Wang, X., & Li, R. (2022). Does population aging reduce environmental pressures from urbanization in 156 countries? *Science of The Total Environment, 848*, 157330. https://doi.org/10.1016/j.scitotenv.2022.157330
Google Scholar Worldcat Fulltext

Wang, Q.-J., Wang, H.-J., & Chang, C.-P. (2022). Environmental performance, green finance and green innovation: What's the long-run relationship among variables? *Energy Economics, 110*, 106004. https://doi.org/10.1016/j.eneco.2022.106004
Google Scholar Worldcat Fulltext

Wei, X., Ren, H., Ullah, S., & Bozkurt, C. (2023). Does environmental entrepreneurship play a role in sustainable green development? Evidence from emerging Asian economies. *Economic Research–Ekonomska Istraživanja, 36*(1), 73–85. https://doi.org/10.1080/1331677X.2022.2067887
Google Scholar Worldcat Fulltext

Xu, J., Moslehpour, M., Tran, T. K., Dinh, K. C., Ngo, T. Q., & Huy, P. Q. (2023). The role of institutional quality, renewable energy development and trade openness in green finance: Empirical evidence from South Asian countries. *Renewable Energy, 207*, 687–692. https://doi.org/10.1016/j.renene.2023.03.015
Google Scholar Worldcat Fulltext

Yuan, B., Zhong, Y., Li, S., & Zhao, Y. (2024). The degree of population aging and living carbon emissions: Evidence from China. *Journal of Environmental Management, 353*, 120185. https://doi.org/10.1016/j.jenvman.2024.120185
Google Scholar Worldcat Fulltext

Yusuf, A. (2023). Dynamic effects of energy consumption, economic growth, international trade and urbanization on environmental degradation in Nigeria. *Energy Strategy Reviews, 50*, 101228. https://doi.org/10.1016/j.esr.2023.101228
Google Scholar Worldcat Fulltext

Zhang, D., Mohsin, M., & Taghizadeh-Hesary, F. (2022). Does green finance counteract climate change mitigation? Asymmetric effect of renewable energy investment and R&D. *Energy Economics, 113*, 106183. https://doi.org/10.1016/j.eneco.2022.106183
Google Scholar Worldcat Fulltext

Zhou, Y., Wang, H., & Qiu, H. (2023). Population aging reduces carbon emissions: Evidence from China's latest three censuses. *Applied Energy, 351*, 121799. Google Scholar Worldcat Fulltext

Appendix A

Table 4

Implicit features of FES-based AI model

No. of functions of deep learning	No. of Features
Model type	Sequential
Random state	42
Activation function	Multiple
Kernel initializer	He normal
Overfittings regularize	l2
Overfitting dropout	0
Optimizer	Adam
Early stopper function	auto
No of patience	10
Callback function	Monitor
Training mode	Auto
Batch size	0
Splitting function	0.2
Maximum number of epochs	1000
Shuffle function	False

An overview of the FES-based AI model configuration and important hyperparameters may be found in Table 4. The Adam optimizer was chosen for its resilience in non-convex conditions, and it was used to execute the optimization process. The research was carried out on a panel dataset, and the shuffling function was disabled in order to show respect for the time-series character of the observations.