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Sustainability, emission trading system and carbon leakage: An approach based on neural networks and multicriteria analysis

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ABSTRACT

Two transitions, green and digital, are changing the operations and strategies of industrial systems. At the same time, businesses are challenged to be globally competitive. Europe has a very ambitious agenda as it aims to be the first climate-neutral continent in 2050. The european emissions trading scheme (EU ETS) has proven to have facilitated the reduction of significant amounts of greenhouse gas emissions, but the risk of carbon leakage is present. This work seeks to explore these issues and their relationships. Through the use of a long short-term memory (LSTM) neural network, a model is built to determine the price of european union allowance (EUA) as a function of different financial energy futures. The results show that the model is very robust and the EUA tends to vary between 78 and 91 €/tCO_2. In addition, a multi-criteria decision analysis (MCDA) is applied to identify the best policy alternatives to enable businesses subject to the EU ETS to be competitive in global markets. The analysis is carried out with the help of academic and industrial experts and it emerges that the criteria considered most relevant are two: (i) public expenditure and its expected benefits and (ii) the industrial ecosystem. The policy implications identify that bonuses should be provided to businesses for innovative solutions that protect both the energy and raw material components. The framework of the 3E (Energy Efficiency, Renewable Energy, and Circular Economy) are critical to businesses' long-term strategies, flanked by digital development.

Introduction

Climate change is the challenge facing all researchers, businesses, public administrations and ordinary citizens. A great gift, the environment in which we live, that is showing significant signs of weakness. The Sustainable Development Goals (SDGs) are a target to aim for, and Europe shows significant differences in performance between countries [1], but the change is at the global level [2].

Major challenges include supporting Industry 4.0 technology, which aims to produce goods with improved efficiency while reducing resource consumption [3], Industry 5.0 and its impact between digital technologies and sustainable practices in supply chain management [4], the changes that sustainability brings about in operations [61], but also the impact of digitalization within supply chain [5]. In a context geared toward proper waste management [6] and emission reduction [7], the goal becomes minimizing the carbon footprint in supply chain [8] also through the material efficiency [9]. Factors that can therefore support projects that reduce emissions are green finance [10], knowledge management [11], and circular supply chain diffusion toward competitiveness [12]. The challenge can be met through sustainable communities that overcome selfishness based on the concept of the sustainable hand [13].

Europe in order to compete in the globalized market with industries that are not subject to additional limits and costs, intends to adopt a carbon adjustment tax at the border [14], but it seems clear that aspects such as renewable energy development, circular economy models, and local industry development need to be combined [15]. In addition, sustainability and digitization can be combined to improve the effectiveness and efficiency of processes [16].

The Europe emissions trading scheme (EU ETS) is a carbon market based on a cap-and-trade system of greenhouse gas (GHG) emission allowances for energy-intensive industries and the power generation sector. It is therefore a pillar of European climate policy. However, to reduce their high levels of GHG emissions some businesses have relocated production outside European borders in order to avoid the stricter European climate regulations. This phenomenon has resulted in CO_2 offshoring, a phenomenon called carbon leakage. This term is also used to describe the context in which EU products are replaced by more carbon-

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intensive imports [17]. The EU has set up a defense mechanism called the carbon border adjustment mechanism (CBAM), which sets a fair price on carbon emitted during the production of carbon-intensive goods entering the EU and serves to encourage cleaner industrial production in third countries. In addition, a number of changes to the existing EU ETS are planned: i) overall reduction of emissions in the relevant sectors by 61% by 2030 compared to 2005 levels (target currently set at 43%); ii) include the maritime sector in the ETS; and iii) expand the scheme to the residential and transport sectors (ETS 2).

The literature shows that few studies have examined the application practices and theoretical research of carbon neutrality [18]. Indeed while carbon capture and storage (CCS) and carbon capture, utilization, and storage (CCUS) can play an important role in this direction, they appear to be limited [19]. Such investments could be fostered by the continued improvement of the carbon trading mechanism [58]. As mentioned above, the EU ETS is based on cap-and-trade and its development is also linked to its flexibility [20]. The European union allowance (EUA) allows businesses to emit one ton of CO_2, and each business is assigned a CO_2 emission limit (cap). The following year, a defined number of EUAs must be surrendered. If this number is less than the assigned cap, the business has the option to sell the EUA (trade). The idea of this system is to create a market for CO_2. So if the price of CO_2 emission permits (carbon price) becomes high enough, some businesses will be induced to green and circular solutions to reduce their emissions rather than paying for allowances.

The literature has evaluated the impacts of the ETS very carefully. Some authors point out that this system has caused regulated businesses to reduce carbon dioxide emissions by 8–12% compared to unregulated businesses [21]. Some empirical results show that the ETS may not have a significant impact on changing the industrial structure, but its implementation promotes the upgrading of the country's industrial structure [22]. It has also been shown that the ETS may lead to an increase in the revenues of regulated businesses [23] and marginal abatement costs are not equal among ETS market participants [55]. The benefits of ETS and its effectiveness in counteracting emission levels is confirmed in other studies [56], which show that their adoption significantly reduces per capita emissions compared to other events, such as oil crises.

To understand the price of carbon, it is necessary to go back to some past studies. Weather conditions, fuel prices, fuel switching and regulation play a significant role in determining the price of carbon [24] and in particular, some analyses show the decisive impact played by fuel prices [25]. As mentioned earlier, several models are proposed that study the relationship between carbon price and primary energy price returns [26], also measuring the impact on economic activity [27]. Some studies have emphasized the relevance of predictive models [28,29] and have applied ETS in other non-European territories [30].

Technological progress plays a key role toward reducing CO_2 emissions [31] and a review of the ETS literature shows the relevance of evaluating policy instruments [32]. This work proposes a novel methodological approach that combines knowledge from the neural network [62] and from multicriteria analysis [33]. Thus, the gap to be filled with this work emerges, namely, to provide a methodological support that can both estimate the price of CO_2 and provide policy suggestions from a strategic analysis on scenarios to reduce the level of emissions. The research objectives are as follows:

- RQ1 - The first objective of this work is to analyze the price of CO_2 shares using a long short-term memory neural network model (LSTM) by correlating it with that of seven other energy commodity stocks. In addition, scenarios based on historical data and future projections are proposed to assess how this price may vary.
- RQ2 - The second objective of this work is to study the perception by energy-intensive industries, thus subject to ETS regulation, of this system. Through the help of a Multi-Criteria Decision Analysis (MCDA), some policy alternatives were hypothesized and the best performing one was identified.

The work is structured as follows. Section 2 proposes the methodology of this work with the description of the LSTM neural network and MCDA with the related inputs used. The results derived from the model based on a historical data set for a period of ten years and the strategic analysis, based on surveys conducted to both academics and industrial actors, is proposed in Section 3. Conclusions are given in Section 4.

Material and methods

The methodology used in this work consists of two different tools (LSTM neural network and MCDA) useful in describing the two distinct research objectives. However, first a simple survey is presented with academic experts on the relationship between the issues of sustainability and artificial intelligence (Section 2.1). After, the neural network is proposed in Section 2.2, while Section 2.3 describes its reference scenarios. Moreover, the multicriteria analysis is defined in Section 2.4, with the scenarios proposed in Section 2.5.

Survey with academic experts

The first phase of this work involves identifying academic experts who will be involved in two separate phases of the survey. In the first they will provide general guidance on the relationship between artificial intelligence and sustainability. In the second to carry out MCDA during the weighting phase. Survey with experts are widely used in the literature [34,35].

Specifically, the ten experts were selected by looking at Scopus profiles of academics who presented at least ten years of experience and had published on sustainability-related topics. An email was sent to several profiles defining the purpose of the project and the methodology used, reminding them that only the first ten positive responses would participate in the panel of experts - Table S1 (of which 20% are women).

The content in the email also specified that the first survey would cover their evaluation on four questions, in which they can assign a percentage value from 0% to 100%. Prior to both surveys, two experts were selected from the ten chosen in order to receive guidance on the content of the survey. Relative to this first stage, no indications emerged. These questions were supposed to assess the issues explored in depth in the two research questions of this work. Below are the four questions:

- Q1. Can artificial intelligence, and specifically neural networks, be a suitable tool for assessing sustainability?
- Q2. Can neural networks be a useful tool for sustainable operations?
- Q3. Can the use of neural networks be useful in assessing the price of CO_2?
- Q4. Can the use of neural networks provide insights into policy interventions related to CO_2 pricing?

Both surveys were conducted between April-May 2023.

Neural network

This work is based on a LSTM neural network, which enables the storage and retrieval of relevant information over time [36,37]. Due to this ability to handle long-term data sequences, they are widely used for time series prediction. The use of a LSTM network was preferred to a classical fully connected neural network because of the better results provided in testing and validation on the chosen dataset.

The dataset was composed by selecting eight variables including one dependent variable, EUA, and seven independent variables related to the former. A choice made in accordance with the reports released by the GSE S.p.A. In addition, to provide a good training process for the artificial intelligence model, data of daily prices of various securities were collected for the past ten years (April 2013-April 2023). This was carried out employing "investing.com" for a total of 2574 data - Figure S1. The independent variables are the stocks: i) Natural Gas Futures; ii) Crude Oil WTI Futures; iii) Heating Oil Futures; iv) Gasoline RBOB

Table 1
Input data - Time series.

No. Scenarios	1 Average 10% higher values	2 Pre-Covid average	3 Average 10% lowest values	4 Average last 3 months
Natural Gas Futures [USD/Mmbtu]	6.741	2.597	1.946	3.280
Crude Oil WTI Futures [USD/Barrel].	106.055	44.539	36.130	76.662
Heating Oil Futures [USD/Gallon].	3.622	1.400	1.132	2.932
Gasoline RBOB Futures [USD/Gallon].	2.958	1.419	1.159	2.493
Brent Oil Futures [USD/Barrel]	111.464	46.515	37.472	82.199
Ethanol Futures [USD/Gallon]	2.386	1.511	1.228	2.161
Natural Gas TTF Yearly Futures [€/MWH].	117.846	15.931	17.798	69.827

Table 2
Input data - Future projections.

No. Scenarios	5 Average last 6 months+ CAGR1	6 Average last 6 months+ CAGR2	7 Average last 6 months+ CAGR3	8 Average last 3 months+ CAGR4
Natural Gas Futures [USD/Mmbtu]	6.295	5.972	4.319	2.730
Crude Oil WTI Futures [USD/Barrel].	2.730	91.573	85.813	81.012
Heating Oil Futures [USD/Gallon].	3.722	4.577	3.096	2.745
Gasoline RBOB Futures [USD/Gallon].	2.810	2.787	2.524	2.588
Brent Oil Futures [USD/Barrel]	97.919	92.698	86.602	82.811
Ethanol Futures [USD/Gallon]	2.315	2.116	2.161	2.161
Natural Gas TTF Yearly Futures [€/MWH].	150.983	322.193	100.916	66.440

Futures; v) Brent Oil Futures; vi) Ethanol Futures and vii) Natural Gas TTF Yearly Futures.

A data cleaning operation, using Phyton code, resulted in a clean dataset. The libraries used to build the network were: i) Pandas; ii) NumPy; iii) TensorFlow; iv) Keras and v) Matplotlib. The dataset is divided into training set (to which 70% of the data is allocated), validation set (25% of the data) and test set (remaining 5%). The network consists of six layers and one final layer. The first layer is a LSTM layer composed of 32 neurons, while the second is a layer, also LSTM, but composed of 16 neurons. The last four hidden layers are fully-connected "dense" layers. Before converging to the last layer with a single output neuron, these are composed of 64, 32, 16 and 8 neurons, respectively. The network has the GlorotNormal kernel initializer and the bias initializer set to zero, while the activation function is "LeakyReLU" for the first three hidden layers and linear for the last hidden layer and the final one. In this work, setting the learning rate to 0.00007 was the result of several attempts and evaluations to achieve an appropriate balance between speed of convergence and quality of results. The same attempts were repeated to set the last two key parameters for the network learning process: i) learning epochs (set to 400) and ii) batch size (set to 128).

Definition of scenarios in the LSTM neural network

Once the model has been built, the next step is to evaluate how the price of CO_2 changes as a function of the inputs provided. Eight scenarios were assumed for this purpose, half of which involve past data and the other half consider the input of growth rates. As for the time series, two of them are constructed on the average of the highest and lowest trends by performing a cumulative analysis of the frequency of occurrence. The weighted average was calculated on the values contained in the highest 10% of values, and the same is replicated for those contained in the lowest 10% of values. The third scenario considers the equally weighted average among the values from the period before Covid, and finally for the fourth scenario the first quarter of 2023 was considered. Table 1 proposes all values identified for the scenarios based on time series only.

Future scenarios, on the other hand, are calculated according to the Compound Average Growth Rate (CAGR). Specifically, three future scenarios start from the average value of the last six months and the last scenario considers that of the last three months. The CAGRs, on the other hand, refer to four different periods, using the traditional review frequency of financial reports (annual, semi-annual, and quarterly) as a yardstick. Table S2 shows the values of the CAGRs and Table 2 the scenarios based on future values.

Multicriteria decision analysis

MCDA is a decision-making process for evaluating and comparing different alternatives based on multiple criteria. This method is widely used in the field of sustainability ([1,38,63]). During MCDA, decision alternatives and relevant criteria for decision-making are identified. A relative weight is assigned to each criterion using the analytic hierarchy process (AHP) [39]. This method is widely used in literature [40]. Next, relevant information is gathered and alternatives are evaluated against the established criteria. Once the alternatives have been evaluated, an aggregation method is applied to combine the weights (row vector) and values (column vector) to produce a final ranking of the alternatives. MCDA value is obtained as the product between the row vector and the column vector.

The method of Saaty [39] defines that the number of criteria should be 5 ± 2; however, the same author proposes the value of Random Inconsistency from 1 to 10 (Table S3). This work considers 10 criteria in order to have a more comprehensive view. Table 3 proposes their list with a related brief description. There is no framework in the literature, so factors that typically characterize sustainability have been identified according to our background. Moreover, in order to give soundness to this choice, they were analyzed by two experts. They were selected from the ten academic experts (Table S1) and no change is proposed for the criteria while some suggestions have been applied for their description in order to facilitate pairwise comparison. All experts were provided the opportunity to have a meeting of up to one hour in which to discuss the criteria and were sent an Excel file containing the criteria descriptions and pairwise comparisons. During AHP, experts could give a value from 1 to 9 according to Saaty [39] - (Table S4). Before handing in the Excel file, it was required to check the value of Consistency Ratio (CR), which

Table 3
List of criteria.

No.	Criteria	Description
C1	Employment impact	The ETS directly affects employment in the sectors where it is applied because it directly represents a cost center and thus a possible cause of cutting back on personnel deemed unnecessary for businesses. In addition, if it were to cause carbon leakage and cause offshoring, it could disincentivize local production and take away local jobs. A high value refers to a higher local employment rate.
C2	Environmental protection	Adoption of strategies that mitigate Greenhouses gases emissions within the atmosphere ensures greater care for the environment and its protection. A high value refers to reduction in emissions.
C3	Investment in technological innovation	Innovation is a central theme of the system. There are two funds, the Innovation Fund and the Modernization Fund, which support this process, and the Cap and Trade system on which the system is based is an additional incentive. A high value identifies a higher level of investment in new technologies.
C4	Cost optimization	Representing a cost center for businesses. Subject to the system, cost optimization is a pivotal activity within corporate strategies to remain competitive in international markets. A high value refers to better use of available resources.
C5	Impact of externalities	The externalities generated by the system are multiple and can be negative (carbon leakage, decreased jobs, less competitiveness of businesses in markets, etc.) or positive (energy efficiency, incentive to use renewable energy, less air pollution and related to it all social benefits such as health and environment). A high value indicates that the positive ones are more significant.
C6	Brand Reputation	Practicing green initiatives is a relevant strategic choice and can influence consumers' and citizens' perception of the brand. Conversely, implementing environmentally harmful initiatives or production practices can negatively impact the business and affect turnover. A high value identifies a benefit to one's business's reputation.
C7	Industrial autonomy	Corporate self-sufficiency must be considered within economic growth and development policies when the system is regulated. A system of taxation, of targeted economic incentives rather than full freedom of action in favor of achieving certain ecological transition goals is something that must be taken into consideration. A business must be enabled to be self-sufficient. A high value indicates that it is more self-sufficient.
C8	Competitiveness in the market	Businesses working under ETS regulation very often operate in international markets where there is a lot of focus on green transition. It is important to protect the business's competitiveness in terms of cost and supply. A high value means that businesses are self-sufficient.
C9	Industrial ecosystem	The ETS includes the various businesses for the sector in which they operate. The aspiration should be to create the conditions for the creation of industrial ecosystems where there are collaborations, cooperation and knowledge exchange among enterprises in respect of the same ecosystems. A high value identifies collaborations, cooperation and knowledge exchange among enterprises in respect of ecosystems.
C10	Public expenditure and expected benefits	State or community intervention with public investment must be compared with the expected benefits of the adopted policy plan. A high value means that the expected benefits are greater than public spending.

at most could be 0.10. This value is calculated according to Random Inconsistency.

Definition of scenarios in the MCDA

The alternatives were chosen to identify five potential scenarios, each of which describes a policy intervention. The goal is to identify which proposals would boost market competitiveness but also how to achieve sustainability goals by reducing emissions. Also at this stage, alternatives were chosen through our background and Table 4 proposes the list of policy alternatives.

A different panel of experts was selected to assign the values, and 10 experts with at least ten years' experience belonging to the industrial sector were identified (20% of them are female). The experts were selected from industry consultants, representatives of Confindustria, and representatives of energy-intensive businesses. The procedure applied is similar to that employed in assigning weights, the difference being that in this analysis the experts must provide values to the alternatives for each criterion examined. The range of values varies from 1 to 10 (thus a 10-point value approach is used) and the survey was conducted always between April and May 2023. Before administering it to the experts, the list of alternatives was validated by two experts selected from the previ-

Table 4
List of alternatives.

No.	Alternatives	Description
A1	No taxation on enterprises that resort to emission offshoring	In this scenario, no additional taxation (such as a tax on imported emissions) is applied to businesses that relocate their emissions. They are given full autonomy of choice regarding the location of production, provided, of course, that existing regulations are adhered to in the local area.
A2	Business taxes to be levied on "imported" emissions from abroad	In this scenario, businesses suffer additional taxation on material and products that are made on "other" territory, thus choosing to relocate production to avoid the additional costs.
A3	Bonus for innovative solutions (renewable energy, energy efficiency) to be applied in a local context for businesses that meet emission reduction targets	In this scenario, incentives in the form of bonuses are provided to businesses that decide to operate in the local area (European in this specific case), with the constraint that they be used to increase the use of renewable energy and improve energy efficiency.
A4	Bonus for innovative solutions (circular economy, material efficiency) to be applied in a local context for businesses that meet emission reduction targets	In this scenario, incentives in the form of bonuses are provided to businesses that decide to operate locally (European in this specific case), with the constraint that they be used to foster circular economies and improve the emission efficiency of materials.
A5	Non-repayable incentives to be applied in a local context for businesses that meet emission reduction targets	This scenario is similar to the last two, but with the difference of not having constraints of some kind in the spending of these funds and leaving strategic freedom to businesses that decide to meet emission targets by producing locally.

ous industrial ten. They were not contributed in the alternatives, while more details are provided in their descriptions.

The last step is to multiply the row vector (obtained by AHP) with the column vector (obtained by 10 point-value) to identify the best-performing alternative measure through a MCDA value.

Results

This section is divided into three subsections. Section 3.1 allows us to assess the relationship between sustainability and digitization according to academic experts. Next, results from the LSTM neural network (Section 3.2) and those derived from the MCDA (Section 3.3) are presented.

Artificial intelligence and sustainability

The framework of this work stipulates, that before proposing MCDA, four questions were posed to academic experts with the aim of evaluating the relationship between artificial intelligence and sustainability. Table S5 collects the different assessments and Fig. 1 proposes the average results. It is worth highlighting two aspects that will also be valid for the other two analyses with experts: i) the respondents all have the same relevance and ii) the rating provided by the expert remains anonymous, so the associated code does not identify any relationship with Table S1.

The analysis of the responses tends to confirm what has been seen in the literature where digital and sustainable development can coexist and thus artificial intelligence can support sustainability [59,41]. On this aspect, therefore, it should be emphasized that the greater availability of data, its optimization plays a role in favor while the social aspect (thus the less control that falls to humankind) and the environmental aspect (since digital data are not exempt from emissions) should always be evaluated. The experts assign the highest score to the question of the role artificial intelligence (and specifically neural networks) can play on sustainability. The experts were keen to point out that this is a crucial research question, which is to identify tools and methods that assess how artificial intelligence affects competitiveness, employment, economic development and environmental impacts. The 91% assigned to Q1 has only one expert assigning the highest value (it should be pointed out that this expert also has the highest values for all the other three questions). Figure S2 shows the distribution of assigned values, and 90% of these values are contained in the 70–95% range. In fact, high values are also assigned to Q2 (84%) and Q3 (82%). Going down in detail from the concept of sustainability in general to that of sustainable operations, the rating tends to be confirmed and there is a slight decrease probably because more emphasis is aimed at economic aspects at this stage. The value that turns out to be very positive is the question on the role of neural networks in assessing the price of CO_2 (which, moreover, corresponds to RQ1 in this work) since it is believed that such models certainly can make their contribution through the study of the relationships between variables, while in-depth analyses are required to assess the goodness of these models, which do not always turn out to be suitable. In this work, the positive impact of LSTM neural networks has been demonstrated. Finally, the question that appears to have the lowest rating is Q4 with 71%, a rating that nevertheless turns out to be positive. So for experts, neural networks with their simulations can provide useful feedback to decision-makers. This question corresponds to RQ2 in this work, and the experts wanted to point out that here the problem turns out to be more complex, since on the one hand the relationship between artificial intelligence and policy implications and on the other hand the relationship between sustainability and policy implications need to be evaluated. In this way, the two RQs are linked by the price of CO_2 and the need to identify quantitative methods to support the decision-maker. In the first, the CO_2 price is calculated using a supporting model developed ad hoc, and in the second, the policy directions that are likely to influence that price are identified.

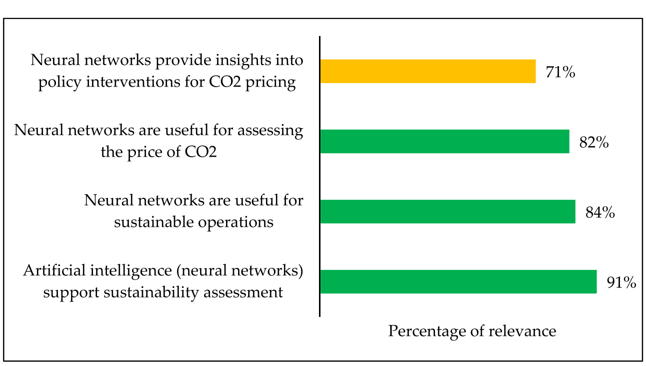

Fig. 1. Opinions on the relationship neural networks and sustainability.

CO_2 price analysis with lstm neural network

The RQ1 of this work is intended to be a support to regulators by showing the potential of artificial intelligence models that are able to capture the relationships between different energy stocks. It emerges how the use of a LSTM neural network is able to capture a correlation between emission prices and other features.

The model was run on the dataset described in Section 2, and two indicators were used to evaluate its goodness-of-fit: i) the loss function and ii) mean absolute error (MAE). When a neural network is being trained, the loss function is a metric used to calculate the error between the model's predictions and the desired outputs. The purpose of the loss function is to reduce this error so that the model can accurately predict new inputs [42]. The MAE, which represents the actual predicted value error, is the average of the absolute errors between the predicted and actual values [43].

A graph of the learning curves was also plotted, as can be seen in Fig. 2. From the graph, where the blue curves are associated with the values of the two functions on the training data and the orange curves with the validation ones, it can be seen that the model generalized the problem well and did not overfitting or under fitting on the data received as input.

In addition, below are the consistent results shown in the validation set and the testing set in terms of absolute value: i) the loss function reported a value of $43.30(€/tCO_2)^2$ on the test data and $58.12(€/tCO_2)^2$ on the validation values and the ii) the mean absolute error reported a value of 4.93 €/tCO_2 on the test data and 5.31 €/tCO_2 on the validation data.

In addition, the value of the slope coefficient of the regression line of the data for the available data from the last 4 months of the dataset, which composed the test set, was also calculated. It emerges that the result of the model turns out to be close to the actual data. In fact, the predicted value is 95.22 compared with the actual value of 97.32. Fig. 3 clearly shows how the analysis of the last one hundred and twenty days between the predicted and the real model shows no significant differences. Thus, the model was able to intercept the pattern present among the features given as input. The choice to compose the test set with the last one hundred and twenty days of the dataset was made precisely to show how well the model performed even in the last period.

The next step was to consider some more recent days downstream of the data used for the dataset, to confirm the robustness of the model. The differences between actual EUA and that predicted by the model are not significant (an example is given in Table S6). Finally, RQ1 is completed by evaluating the scenarios proposed in Section 2.3. This allowed the model to make a prediction on these data and see how the price of carbon packages would react to changes in the prices of other features - Fig. 4.

From the results, it is possible to deduce that the value of features significantly influences the EUA price. The range, in fact, tends to fluctuate by about 80 €/tCO_2. On the one hand, the minimum values occur in scenarios 2 and 3, i.e., those that occur for the minimum value of

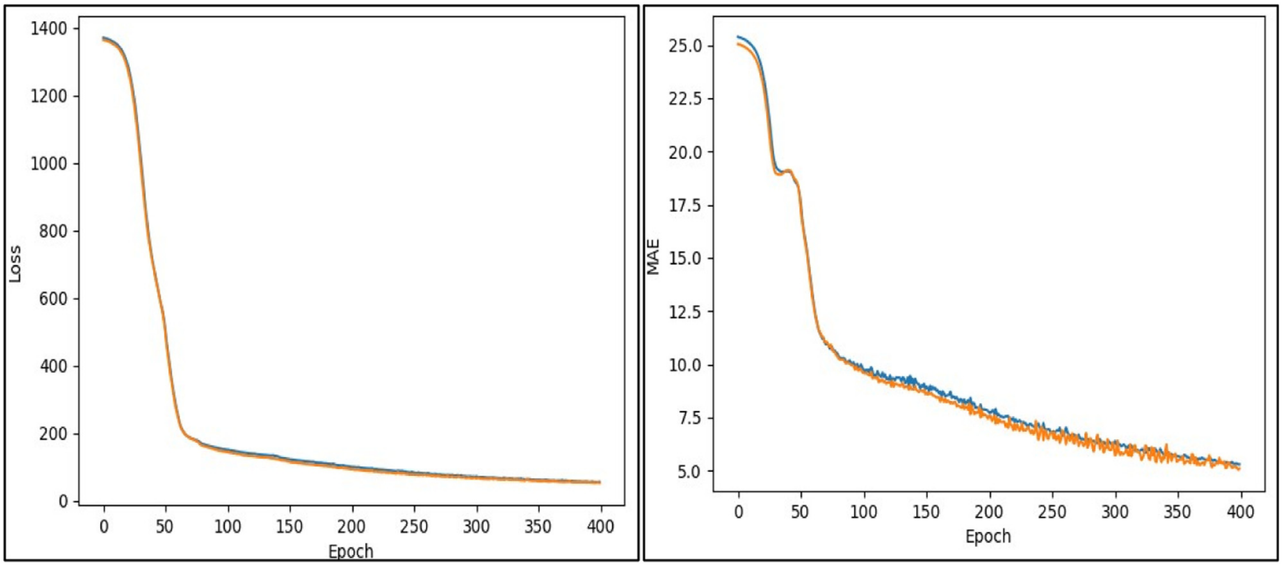

Fig. 2. Graphical trend of loss function and MAE during the model-training period in the various epochs.

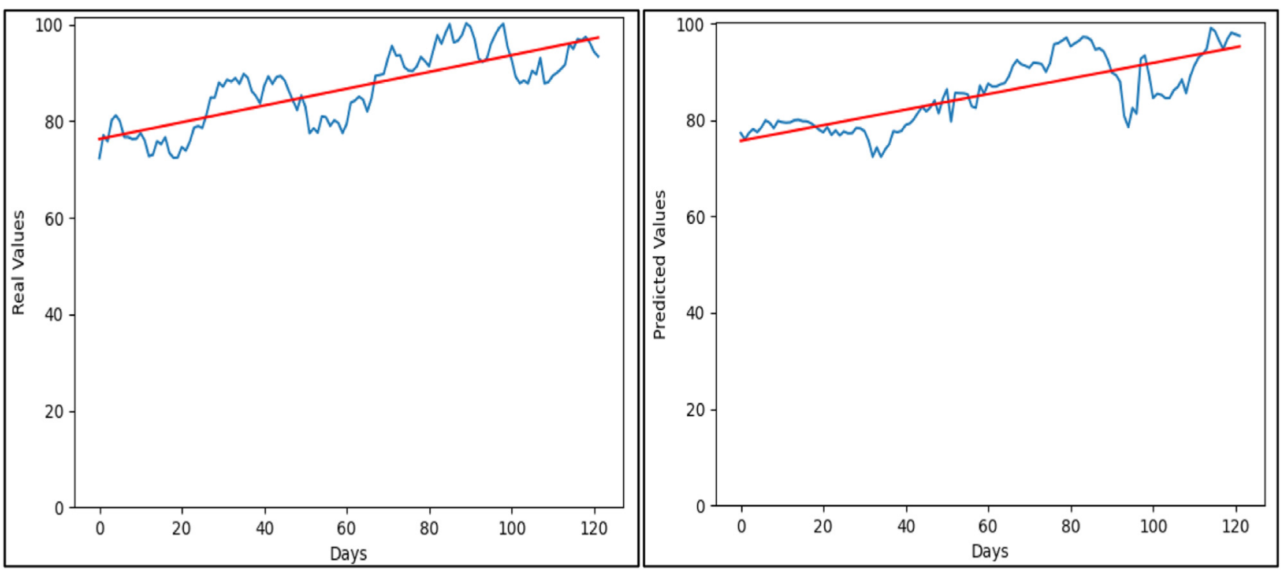

Fig. 3. Actual values and values predicted by the model for the last one hundred and twenty days of the dataset. All values are reported in €/tCO_2.

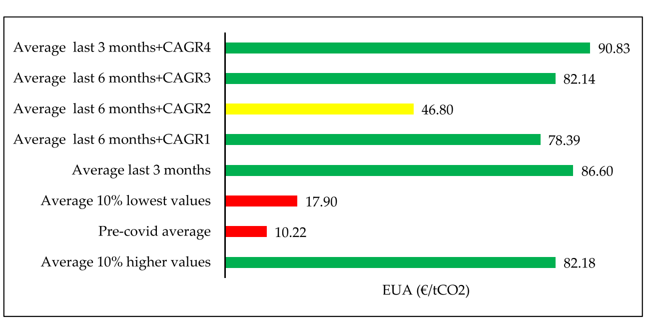

Fig. 4. Results of model predictions.

the historical data (result therefore expected) but also that for the pre-Covid period. The first consequence that emerges is that the pandemic framework has not only generated the deaths of many people, but also significantly changed the international picture. The challenges of sustainability were discussed earlier, and probably having to restart civil society from the lesser certainties that Covid brought about, the new economic model from which to restart is one that defends ecosystems. Such prices are therefore currently unrealistic. The model determined them solely because they refer to historical frameworks. The interesting fact is that the maximum value of the EUA price does not occur with scenario 1 since there are as many as two other scenarios in which the value is even higher. If in fact scenario 1 concerned the maximum value and was therefore expected (about 82 €/tCO_2), scenario 4 confirms how the current trend follows a strong surge in energy costs and this also pushes the EUA value higher than the previous mentioned scenario (about 87 €/tCO_2). This value opens up for reflection, namely whether the high carbon price is able to push the various industrial and non-industrial activities to put the general welfare at the center of their agenda [44]. However, at this first stage, the model determines an output through the LSTM neural network and does not provide policy suggestions. Having examined scenarios based on historical data, we now evaluate future scenarios. Here scenario 8 (about 91 €/tCO_2) stands out, which is based on the most recent average value but also on the CAGR relative to the last period. A value that starts to register at the actual value following the months following the examined dataset. This again confirms how the model is able to provide important estimates. High values are also found in scenarios 7 and 5 (78–82 €/tCO_2) in which the starting value was that before the closest period (the six-month period and not the quarter was taken as the starting point).

Comparison with data from the literature is not straightforward. In fact, some older works do not show low values because the models were unsuitable, but because ways to mitigate climate change were being indicated that were not actually undertaken. Similarly, the low price that was associated with the value of the EUA (also verified by our data) did not stimulate businesses to reduce emissions, since in this case where they were in default their cost would be incurred. The analysis shows values as low as 10 €/tCO_2 [45] in which an unsuitable value was shown to counter the current carbon-based economy and 35 USD/tCO_2 [57]. Higher values were proposed in other studies: 50 €/tCO_2 [46] and 50 USD/tCO_2 [60]. However, more significant values were proposed by Stiglitz et al. [47] who identified 40–80 USD/tCO_2 by 2020 and 50–100 USD/tCO_2 by 2030. More recent work shows that values could be even more significant, as the 55% mitigation ambition target in the EU could lead to tripling (NEMESIS) or quintupling (EU-TIMES) carbon prices by varying between €59–1,87$_{2,010}$ /tCO_2 and €120–575 /t$CO_{2\ 2010}$ [48]. Other studies show values similar to those proposed in this work, namely 45–94 €/tCO_2 [54] and 80 €/tCO_2 [49], which are higher than 18–53 €/tCO_2 [50].

However, the work has technical improvements that could be applied on neural networks, and obviously the dataset could always be enriched with new data.

Strategic analysis: ETS and policy implications

Analytic hierarchy process

The first step of MCDA is to assign weights in order to calculate the row vector. The ten academic experts provided their ratings, and in analyzing their data, the first step was to verify that all proposed CRs were not greater than 0.10. Once this verification was done, the different data were examined (Tables S7–16) and then aggregated (Table 5).

From the analysis of aggregate data for four out of ten experts, criterion C10 (public expenditure and expected benefits) was rated the most important. Two experts assigned the highest importance to criteria C3 (Investment in technological innovation) and C9 (Industrial ecosystem), respectively. Finally, criteria C7 (Industrial Autonomy) and C8 (Competitiveness in the market) are also found to excel once. However, the advantage of multicriteria analysis is to consider different opinions. It stands out, for example, that for one expert, one of the above criteria (C3) is the least relevant. However, there is greater convergence on criteria C1 and C2, namely employment impact and environmental protection, which turn out to close the ranking in 3 cases. Brand reputation (C6) turns out to be the lowest value in two evaluations. The next step is to average each criterion according to the ratings provided by the experts - Fig. 5.

The results show that academics believe there are two criteria that are worth one-third of the entire mix of criteria. The basic idea is that businesses can be competitive by including green and circular resources within their production mix, but also by joining forces at the local level.

In this way an industrial ecosystem can be created (0.142), but this turns out to be successful if public money is spent on projects that really support sustainability (0.174). Thus, that myth, typical of the political world, which having budget at hand is an element of success is dispelled. In fact, if this public money is not used for projects that improve the general welfare, the risk run is of inefficient public spending. This is where the term sustainable spending comes in, which is that community money, obtained through taxes and contributions, is reinvested for the welfare of all by achieving a virtuous chain. Any action that protects the interests of a few would result in an unsustainable attitude.

Analyzing the top positions, criterion C3 (0.095) does not appear, on which, in addition to the minimum value given by an expert, other non-significant evaluations weigh in.

The three criteria that proceed it complete the puzzle described above, as the idea that should emerge is that the achievement of the goal is not only achieved by following the success criteria, but also by giving relevance to the others. Competitiveness (0.114) is a goal that businesses set for themselves, and regulatory systems cannot create market distortions. It is therefore necessary for the rules of the game to be equal. In this direction, it is necessary to reduce different taxation among countries, but also not to create preferential paths for certain sectors.

Tied at 0.101 we have two criteria. Externalities, because if they can be included in the value chain, an attitude of the production side that

Table 5
Aggregation of weights.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
C1	0.077	0.058	0.064	0.058	0.038	0.077	0.034	0.0629	0.087	0.048
C2	0.050	0.099	0.042	0.047	0.052	0.171	0.046	0.0820	0.148	0.072
C3	0.058	0.077	0.056	0.176	0.222	0.099	0.072	0.0720	0.050	0.064
C4	0.113	0.113	0.088	0.077	0.044	0.058	0.063	0.0546	0.058	0.057
C5	0.099	0.050	0.073	0.147	0.120	0.129	0.082	0.1108	0.067	0.131
C6	0.067	0.067	0.049	0.077	0.059	0.050	0.040	0.0502	0.113	0.035
C7	0.087	0.148	0.105	0.077	0.068	0.067	0.150	0.1437	0.077	0.083
C8	0.129	0.171	0.169	0.099	0.144	0.087	0.081	0.0971	0.099	0.058
C9	0.148	0.087	0.148	0.113	0.077	0.148	0.192	0.1225	0.171	0.209
C10	0.171	0.129	0.205	0.128	0.176	0.113	0.240	0.2041	0.129	0.243

Max weight Min weight

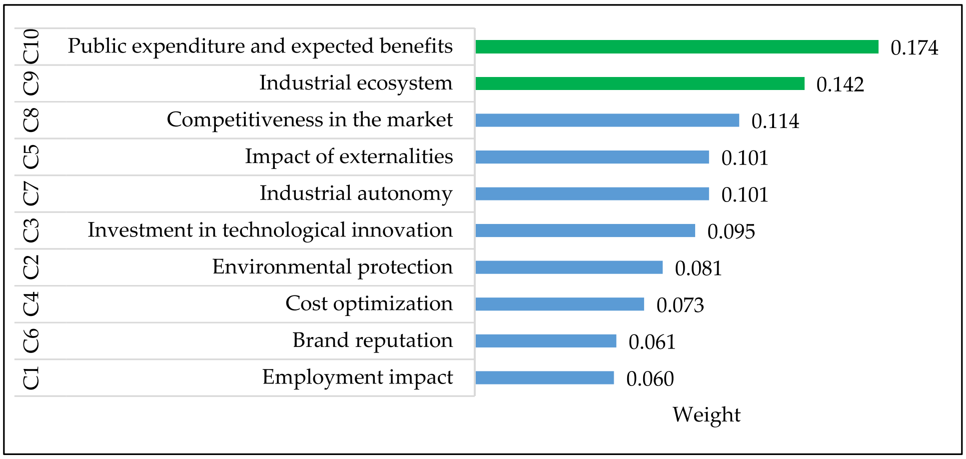

Fig. 5. AHP results - row vector.

is more synchronous with sustainability goals is inevitable. Industrial autonomy demonstrates how strong the need is to be able to manage its resources without external intervention that could typically undermine long-term strategies.

In fact, this last criterion combined with industrial ecosystems describe that complex world of doing business, characterized by multiple risks, where the goal is to have no interference from the state. Environmental protection (0.081) receives less attention because this criterion probably makes it explicit in a direct way, but it turns out to be an indirect aspect linked to other criteria as well. A similar argument applies to cost optimization (0.073). The ranking is closed by the social aspect, related to employment impact (0.060). Probably, there is always a tendency to think that this criterion is closely related to the others and is not placed at the center of the agenda.

However, this weakness on the social side, should open serious reflections and welfare should be revised in order to reconcile the needs of workers with those of the organization. The value on brand (0.061) is identical, as one gets the idea that businesses even if they do not actually follow actions to protect the environment are still able to remedy it. However, it should never be forgotten that brand can have a very significant value, an achievement achieved with sacrifice. At the same time, in the case of an action deemed very unethical, its value can decrease quickly and significantly.

Assessment of policy alternatives

The second step of MCDA is to assign values in order to calculate the column vector. In this phase, industrial experts provide a value on the criteria by evaluating individual policy alternatives. Using the 10-point value the different contributions are collected (Tables S17–26) and it is uniquely verified that values in the range 1–10 have been placed, from which we can evaluate their distribution (Figure S3). The peak is concentrated for values 7 (20%) and 8 (21%) and it emerges that 86% are contained in the range 5–10. This data indicates that the alternatives appeared to be consistent with climate mitigation goals. Table 6 proposes the aggregate data.

The assignment of values shows that the maximum value for almost all criteria concerns alternative A3 with a value above 8 for criteria C2, C3, C6 and C7 and close to 8 for C9 and C10. The lowest of the maximum values is that associated with criterion C1 equal to 7.3. As for criterion C5, however, alternative A4 prevails. As far as minor values are concerned, primacy belongs to alternative A1 for five criteria, while alternatives A5 and A2 have it in three and two criteria, respectively.

Table 6
Aggregation of values - column vector.

	A1	**A2**	**A3**	**A4**	**A5**
C1	3.80	7.10	7.30	7.00	6.40
C2	5.30	7.80	8.40	7.50	6.60
C3	5.40	6.30	8.20	7.10	7.10
C4	6.40	6.00	7.60	7.00	5.10
C5	6.20	5.70	7.90	8.10	6.80
C6	4.60	6.20	8.40	7.80	7.00
C7	5.70	7.00	8.50	7.70	7.30
C8	7.30	6.70	7.70	7.60	6.20
C9	6.10	5.20	7.90	7.70	5.60
C10	5.20	7.20	7.90	7.50	5.10

Max value Min value

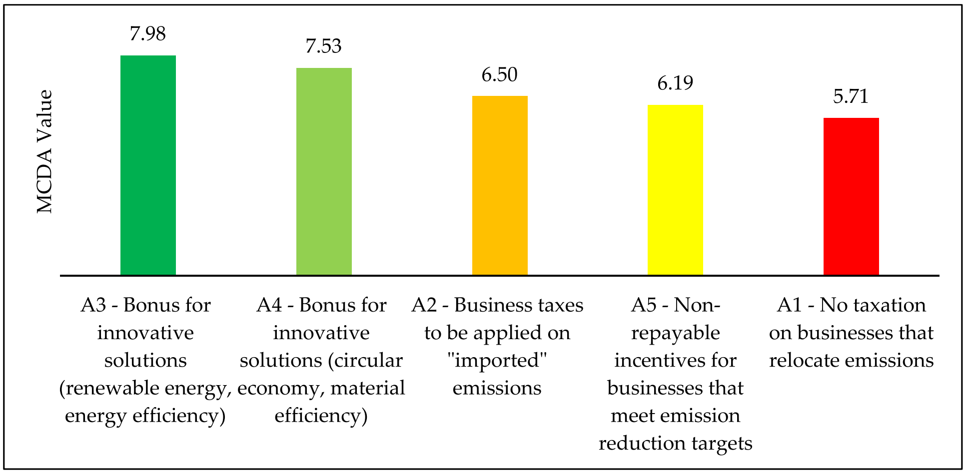

Fig. 6. MCDA Value.

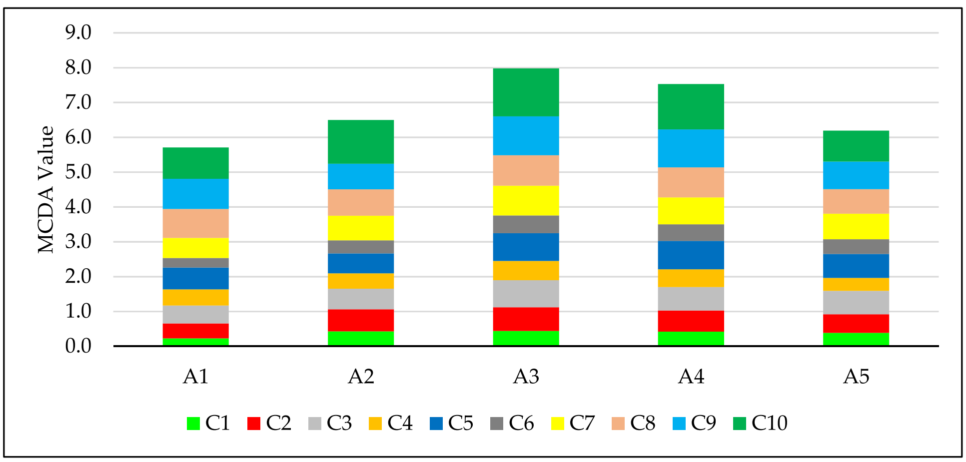

Fig. 7. Decomposition analysis - MCDA value.

The assignment of values is unrelated to that of weights, and being also characterized by a different panel of experts, some differences/similarities can be noticed. Criterion C1, considered as the least relevant by academics, is found to have the lowest value by the panel of industrial experts in three alternatives (A1, A3 and A4). For alternative A2, the lowest value is associated with criterion C9, which occupied the second position in the ranking, and this will result in a negative impact on the overall value. The same applies to alternative A5, which has C10 as the criterion with the lowest value in addition to C4, i.e., the most relevant in the ranking. Evidently even more than the previous case, this data will negatively affect the overall result. The highest value analysis is criterion C7 for alternatives A3 and A5, C8 for alternative A1, C2 for alternative A2, and C5 for alternative A4. This data will positively influence the overall result considering that these criteria are the most relevant after criteria C9 and C10. An interesting finding is that of brand reputation, which is little considered by academics, re-evaluated by industrialists particularly for alternatives A3, A4, and A5.

MCDA value and policy implications

The last step in MCDA is to multiply the row vector obtained in Fig. 5 with the column vector proposed in Table 6. The results are proposed in Fig. 6, where three shades of color are identified: green indicates fully promoted alternatives, yellow those that achieve sufficiency, and finally red indicates those that are not quite correct.

The results see innovative solutions concerning interventions on energy issues (such as renewable energy and energy efficiency) excel with a value of 8 and on raw material recovery (circular economy models, optimal use of resources) with a value of 7.5. This result identifies the successful direction of the sustainability model that aims to create a low-carbon economy whose primary goal is to reduce emissions but create economic development and employment opportunities. Businesses can change the way they produce by placing ecosystem balance at the center of their agenda. However, it is not only necessary to center SDG 13 (Climate Action) by focusing on innovation in industrial systems by aiming to achieve SDG 9 (Industry, Innovation and Infrastructure), but also to consider other goals such as SDG 7 (Affordable and Clean Energy) and SDG 12 (Responsible Consumption and Production) - [44]. So in this framework, the great change of businesses can also be triggered by the demands of citizens, who increasingly point to sustainable choices. However, sustainable products/services cannot have a cost that is unaffordable to citizens, and it is what is necessary for there to be effectiveness and efficiency in the costs of businesses such that they can apply low mark-ups making their products/services affordable. The positive impact of renewables [51] and energy efficiency [52], on par with the circular economy [53] on reducing emissions and the reflection they have on the ETS appears to be confirmed by the literature.

The next step is to contribute to the transformation of businesses through bonuses that are paid according to the actual and potential emission reduction values that can be achieved. Our goal is to build a society in which through the subsidies provided to green and circular solutions they become competitive with high-impact resources over time in order to rely less and less on public support. The results therefore tend to reward incentive systems through the provision of bonuses that businesses can invest in their best way in order to have consistency with their strategic choices and be able to structure long-term choices.

The scenario that garners a rating below sufficient is Alternative A1 (with a value of 5.7), which is the one that provides no taxes to businesses that resort to offshoring. Thus, on the one hand, there is a tendency to reward those who want to make green investments rather than taxing those who move in the opposite direction, fostering the risk of carbon leakage.

The focus on sustainability is also confirmed by the third place applied to alternative A2 (with a value of 6.5), comparable to the implementation of CBAM in the coming years. Thus taxing businesses that "import" emissions from abroad. Finally, in penultimate place is alternative A5 (with a value of 6.2), which provides non-refundable incentives (thus without specifying the actual use) for virtuous businesses, i.e., those that aim to reduce their level of emissions out of an ethical sense.

In order to give robustness to the results, a different scenario was also considered in which the alternatives were evaluated by assigning equal importance to the criteria. There is not some variation in ranking among the five alternatives, and the MCDA values deviate no significantly.

Moreover, it is possible to do a disaggregation of the results (Fig. 7-Table S27). The two criteria (C10 and C9) that excelled in the AHP impact 30–31% of the MCDA value of all alternatives except A5 (it stops at 27%). The weight of these two criteria was 31.6% in the AHP. So the experts by not assigning the highest values to these two criteria did not make these criteria impact even more significantly. It is worth mentioning that the industrial experts, were not aware of the weights assigned by the academic experts.

Conclusions

The pandemic period has altered the lives of all of us, as many certainties have broken down. The issue of sustainability has now come out of the corner in which it has been kept for too long, as the balance of ecosystems is currently unverified and climate change has become an objective fact.

In this framework for businesses to make profits while also creating social employment and respecting the environment becomes increasingly complex but feasible. However, where regulation is stringent and tends to disadvantage some territories over less regulated ones, the principle of free competition is lost. Europe wants to be sustainable, but also inclusive and resilient. The EU ETS has produced important results and this work places it at the heart of its agenda.

From a methodological point of view, the advantage of the LSTM neural network is introduced, which shows excellent results and is proposed as a tool to support regulation. At the same time, MCDA is confirmed to be a useful tool in decision-making processes.

From an operational point of view, it appears that the EUA tends to have values ranging from 78 to 91 €/tCO_2 following current trends. Where the cost of carbon is high, businesses have an additional reason not to pollute. However, businesses need to be supported and should be proposed as places where they want to adopt the sustainable hand model from the ground up. The AHP results proposed by academics show that the most relevant criteria are public spending and industrial ecosystem. These criteria weights, combined with the values given by the industrial experts allow for the calculation of a MCDA value for the policy alternatives examined. Again, the results are very clear: development of the 3E model is capable of making businesses globally competitive. Thus it is necessary to provide bonuses for innovative solutions involving energy efficiency, renewable energy and circular economy models. Similarly, the path to CBAM turns out to be correct, as it is deemed fair to penalize those who import emissions. The risk of carbon leakage should not be underestimated. The results integrated by academic and industrial experts indicate that there is a common goal, which is to make public and private investments sustainable, keeping European businesses competitive in global markets. Only then will the European model be replicated and applied to the rest of the world and climate neutrality goals achieved.

This work shows the need for greater openness to artificial intelligence for sustainability purposes as well, but supporting analyses are needed. In this context, the social dimension should not be underestimated. Academic experts point out that digital development can be supportive of sustainability and specifically sustainable operations. Neural networks are found to be very useful for defining EUA and also show a moderate result for supporting policy-makers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.susoc.2023.08.002.

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