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Profitability and SDG 13-Climate Action: The Moderating Role of Environmental Management Training: A Machine Learning Approach

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ABSTRACT

Research background: This study examined the critical intersection between corporate profitability and adherence to Sustainable Development Goal (SDG) 13 - Climate Action, highlighting the importance of environmental management training within organizations. As the global business landscape evolves, it is essential to understand how internal sustainability practices influence financial outcomes. This research addressed the gap in understanding the dynamic interplay between corporate financial performance and strategic commitment to environmental sustainability.

Purpose of the article: The primary objective of this research was to analyze the moderating role of environmental management training on the relationship between firm profitability and support for SDG 13. It attempted to elucidate how structured training initiatives can improve corporate financial performance while promoting robust climate action strategies.

Methods: This study used a comprehensive panel dataset of 31,346 firms in 67 countries from 2013 to 2022. Advanced machine learning algorithms, including decision tree, random forest, gradient boosting, and logistic regression, were employed to analyze the impact of environmental management training on corporate profitability and sustainability initiatives. These methods allow for a nuanced understanding of the complex, non-linear interactions among the variables studied, providing deep insights into the dynamics at play.

Findings & Value added: The results indicate that certain predictive models, such as Decision Tree and Random Forest, initially faced challenges like overfitting. However, incorporating environmental management training variables improved their robustness, highlighting the importance of variable selection in sustainability analytics. Among the models tested, Gradient Boosting demonstrated a strong balance between precision and recall, making it particularly effective for predicting corporate engagement in climate initiatives. The incorporation of machine learning provides a novel methodological perspective that deepens our understanding of how profitability metrics can influence and enhance corporate sustainability efforts. This research adds value to the discourse on sustainable business practices by providing robust empirical evidence and methodological innovations that can guide policymakers and business leaders in crafting strategies that promote sustainable development. Moreover, this study aligns with the journal's focus by offering innovative approaches to economic policy and enhancing understanding of the intersections between corporate strategy and sustainable business practices.

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INTRODUCTION

In today's dynamic business environment, the United Nations Sustainable Development Goals (SDGs) serve as a foundational framework for addressing the myriad sustainability challenges facing the world. Among these, SDG 13 - Climate Action - stands out as a pivotal goal, urging businesses to reduce their environmental footprint and actively combat climate change (Boffa & Maffei, 2021). This paper strived to unravel the intricacies of the relationship between corporate profitability and commitment to SDG 13, examining the moderating effects of environmental management training and teams within organizations.

Emerging research suggested that strategic environmental initiatives not only meet with ethical mandates, but also improve financial performance, creating a virtuous cycle in which increased profitability enables greater investment in sustainable technologies and practices (Huong et al., 2021; Lee, 2012). This relationship is critical because increased profits provide the resources needed to implement comprehensive environmental strategies, which are critical under SDG 13. These strategies include adopting sustainable energy solutions, building resilient urban and rural ecosystems, and protecting biodiversity, all of which are essential for sustainable development amid growing global food security concerns (Fidler & Noble, 2013).

Furthermore, the importance of environmental management training is increasingly recognized as a critical factor in fostering an organizational culture that supports sustainability goals. This training not only boosts employee motivation but also equips them with the necessary skills to effectively implement and optimize environmental strategies, thereby increasing the company's overall profitability and its ability to contribute to climate action (Cassells & Lewis, 2021).

This study posited that the synergy between profitability and proactive climate action through SDG 13 is multifaceted and enriched by organizational practices in environmental management. By exploring how environmental management training and teams influence this dynamic, the research aimed to provide new insights into how companies can effectively align their financial goals with their sustainability commitments, thereby furthering their ability to meet and exceed the targets set forth by SDG 13.

The examination used machine learning techniques to explore the complex interplay between profitability, environmental management practices, and the moderating role of environmental management training. The use of machine learning allowed for the identification of non-linear relationships and the detection of patterns that may not be apparent using traditional statistical methods.

The study addresses the central research question: How does environmental management training moderate the relationship between corporate profitability and engagement in SDG 13 (Climate Action)? Building on this inquiry, the hypothesis posits that environmental management training strengthens the alignment between profitability and climate action initiatives by fostering organizational capabilities to identify and leverage synergies between economic and environmental goals. To investigate this, the examination employed machine learning techniques to explore the complex interplay between profitability, environmental management practices, and the moderating role of environmental management training. Unlike traditional statistical methods, machine learning enabled the identification of non-linear relationships and latent patterns, offering deeper insights into how training interventions reshape the dynamics between financial performance and climate-related commitments. By analyzing large-scale datasets, the study sought to uncover whether—and under what conditions—environmental management training acts as a catalyst for translating profitability into measurable progress toward SDG 13.

The findings of this study contributed to the existing literature by providing empirical evidence on the role of environmental management training in improving the relationship between profitability and environmental sustainability. The implications of this research could be valuable to both academics and practitioners seeking to understand the drivers of corporate environmental performance and the strategies for achieving sustainable business growth.

The organization of this paper was structured to meticulously explore the intricate relationships between corporate profitability and SDG 13 - Climate Action, specifically through the lens of environmental management training. It began with an introduction, which set the stage by highlighting the critical importance of empirical research in understanding how corporate sustainability practices affect their financial outcomes. This was followed by a thorough literature review that examined recent scholarly contributions that have explored the impact of environmental strategies on firm performance. The paper then described the research objectives, outlined the data collection methodology, and discussed the hypothesis formulation and testing processes. A detailed section on respondent demographics was also provided. The core of the paper presented the empirical findings, detailing the statistical hypothesis evaluation process and offering an economic interpretation of the results. This was followed by a brief discussion of the main findings. Finally, the conclusion summarized the main findings, acknowledged the limitations of the study, and suggested future research directions in the area of corporate sustainability and profitability.

THEORETICAL BACKGROUND

The relationship between environmental management practices and financial performance has been examined from a variety of perspectives, with mixed results. Research such as that of Albertini (2013) and Erekson et al. (2008) highlighted a positive relationship, where environmental investments improve financial outcomes through cost reduction, risk mitigation, and enhanced corporate reputation. However, other studies, including Albertini (2013) again, presented a counter-narrative, suggesting that the immediate costs of environmental initiatives may exceed their financial benefits, resulting in a neutral or negative impact in the short term.

Other literature highlighted the profitability benefits associated with certain environmental practices. Kumar & Dua (2021) found that measures such as energy efficiency and waste reduction not only save costs but also improve market valuations. Integrating environmental knowledge and training as part of green human resource management also increases eco-efficiency, which has a positive impact on firm profitability (Martínez-Ferrero & García-Meca, 2020).

Leadership and training in environmental management have significant implications for sustainable business performance. Eco-transformational leadership, coupled with focused eco-training, enhances organizational sustainability (Su et al., 2020). These elements of green human resource management, particularly training, are critical to improving individual and overall environmental performance, further strengthened by organizational support.

Studies showed a mixed impact of green management on financial performance, influenced by different moderating factors such as environmental management training and teams (Molina-Azorín et al., 2009; Basuony et al., 2023). These elements not only improve environmental performance but also create synergies that improve financial results. Contextual factors such as regional regulations, stakeholder pressures, and sector-specific requirements further shape these results (Albertini, 2013).

The adoption of environmental, social, and governance (ESG) practices has been linked to improved financial performance, particularly in the context of climate change. Research indicates that firms increasingly recognize their economic obligations alongside their legal and ethical responsibilities to mitigate climate risks. The use of machine learning to predict firm-level climate change risks and the adoption of ESG practices underscores the importance of integrating sustainability into corporate strategies (Khan, 2024). The role of environmental management training as a moderating factor in this dynamic cannot be understated. Training programs that focus on sustainability and environmental management equip employees with the necessary skills to implement ML-driven strategies effectively. Such training fosters a culture of sustainability within organizations, enabling them to leverage ML tools for better decision-making regarding climate action (Debnath, 2023).

This study conducted a comprehensive literature review to examine the moderating role of environmental management training and teams in the interplay between environmental and financial performance. It considered regional, sectoral, and temporal factors to provide a detailed understanding of how sustainability and profitability intersect to inform business strategies and policy decisions. The paper hypothesized that corporate profitability, as measured by return on assets (ROA), is positively correlated with support for SDG 13 Climate Action, a relationship that is enhanced by effective environmental management training and teams.

RESEARCH OBJECTIVE, METHODOLOGY AND DATA

This study aimed to explore the effectiveness of environmental management training as a moderating factor in the pursuit of Sustainable Development Goal 13, Climate Action, by analyzing its impact on corporate engagement and profitability. Specifically, the research strived to unravel the complex interactions between firm characteristics - including size, financial metrics, and environmental performance - and the implementation of SDG-13. Through the use of machine learning techniques, this study systematically assessed non-linear relationships between a wide range of variables, such as environmental performance score, environmental impact score, firm size, financial metric such as return on assets (ROA) and return on equity (ROE), and governance factors including leverage, capital expenditures, board size, CEO duality, board tenure, executive compensation, audit committee independence, and board gender diversity. In addition, the study focused on the interactive effects between environmental management training and key financial performance metrics (ROA and ROE) to assess whether such training not only improves financial outcomes but also fosters more robust environmental stewardship. By integrating advanced analytical techniques and comprehensive data, this research aimed to provide deep insights into the strategic benefits of incorporating sustainability training into corporate practices, ultimately contributing to the global efforts to achieve effective climate change mitigation strategies.

The dataset used in this study was a comprehensive panel dataset spanning from 2013 to 2022, covering firms from 5 regions of the world, including 67 countries in total. This dataset included both financial and non-financial firms, segmented by a total of 11 industries, and indexed under unique identifiers (ISIN) for each firm over 9357. The study focused on companies' engagement in environmental, social, and governance (ESG) practices, which are central to integration of Sustainable Development Goal 13 - Climate Action.

The sample selection aimed to provide a holistic view of the impact of environmental management training on firms' profitability and adherence to SDG 13. It included various metrics such as return on assets (ROA), return on equity (ROE), firm size, and leverage, as well as ESG scores reflecting the firms' commitment to environmental and social responsibility. Additional dimensions, such as board characteristics and gender diversity, were assessed for their moderating effects on the relationship between profitability and climate action initiatives.

In this study, several supervised machine learning algorithms were used to investigate the relationship between profitability and SDG 13 - Climate Action, under the moderating influence of environmental management training. The selected algorithms included decision tree, random forest, and gradient boosting classifiers, as well as logistic regression. These models were chosen for their ability to effectively handle binary and multi-class classification problems and provide a robust framework for predicting categorical outcomes based on a set of predictor variables (Dahlmann et al., 2017).

The decision tree classifier served as a fundamental model, providing clear visualizations of decision paths that can be easily interpreted even by non-experts. Despite its susceptibility to overfitting, it provided a reasonable basis for comparison with more complex algorithms.

The random forest classifier, an ensemble of decision trees, was configured with 200 trees and no maximum depth to allow the trees to fully expand based on information from the data (Talukder et al., 2023). This model was particularly appreciated for its performance and robustness to overfitting due to its ensemble approach, which averages multiple deep decision trees trained on different parts of the same training set (Xia et al., 2020). The study's adopted minimum sample splits of 2, ensured minimal leaf size, allowing the model to capture sufficient detail in data patterns.

The gradient boosting classifier was used to sequentially build trees, where each successive tree focuses on the errors of the previous ones, thus sharpening accuracy and improving the model's performance on complex datasets. Configured with 100 estimators and a random state for reproducibility, this model is highly regarded for its predictive power in competitive machine learning tasks.

Finally, logistic regression was used due to its efficiency and simplicity in modelling binary outcomes (Huerta-Soto et al., 2023). With maximum iteration of 1000, we ensured that the optimization algorithm converged (Dahlmann et al., 2017). The performance and explainability of these models were evaluated to provide insights into the complex relationship between profitability, environmental management training, and climate action commitment (Çelik et al., 2022).

The selection of algorithms for this study was guided by their suitability for analyzing corporate engagement and financial governance data. A decision tree was chosen for its interpretability, allowing for a clear understanding of decision-making pathways in corporate engagement (Luna et al., 2019). Random forest was incorporated due to its robustness against overfitting and its ability to handle high-dimensional financial and governance data, ensuring reliable insights. Additionally, gradient boosting was included for its high predictive accuracy and iterative error refinement, enhancing model performance (Vanhaeren et al., 2020). Logistic regression served as a benchmark, given its simplicity and effectiveness in binary classification problems. Notably, random forest's ensemble learning capabilities further mitigate overfitting, ensuring a more reliable analysis of the interactions between financial performance, ESG factors, and climate action commitments. These methodological choices collectively strengthen the study's analytical framework, balancing interpretability, accuracy, and robustness (Manley, 2023).

RESULTS AND DISCUSSION

Descriptive statistics

In the comprehensive dataset of 31,346 firms, the authors observed significant heterogeneity across several key sustainability and financial performance metrics. The data showed an average support level of 0.33 for SDG 13 (Climate Action), indicating that approximately one-third of the firms are actively engaged in sustainability initiatives aligned with this goal. Notably, the average environmental performance and impact scores (EPScore and EIScore) were 37.64 and 24.26, respectively, indicating significant variation among companies in their environmental efforts. Financial indicators such as return on assets (ROA) and return on equity (ROE) further illustrated the financial disparities, with mean score of 15.84 and 2.79, respectively, which are critical to sustainable practices (see table 1).

The analysis also revealed significant diversity in governance structures and management practices, as reflected in the ranges of board size and CEO duality. In addition, the variability in executive compensation and board

Table 1: Descriptive Analysis

Statistic	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
mean	0.33	37.64	24.26	15.84	2.79	3.32	25.03	11507	9.22	0.33	1.82	8.46	85.91	0.48	22.93	2.24
std	0.47	28.28	30.56	2.66	16.91	380.06	19.07	2036171	3.09	0.47	0.57	2.1	23.23	0.5	14	4.06
min	0	0	0	7.7	-489	-37832	0	0	1	0	-3.22	-10.2	0	0	0	-29.1
25 %	0	10.89	0	13.97	1.01	1.59	8.79	1	7	0	1.48	7.28	75	0	12.5	1.14
50 %	0	36.2	0	15.62	4.16	9.54	23.43	3	9	0	1.86	8.46	100	0	22.22	2.29
75 %	1	61.25	50	17.38	8.35	17.42	37.4175	6	11	1	2.22	9.56	100	1	33.33	5.53
max	1	99.05	99.89	28.31	253.09	31560	175.99	361000000	138	1	3.59	22.51	100	1	100	24.48

Note: 1. Sustainable Development Goal 13 (SDG_13_D), 2. Environmental performance score (EPScore), 3. Environmental impact score (EIScore), 4. Firm size (Firm_SZ), 5. Return on assets (ROA), 6. Return on equity (ROE), 7. Leverage, 8. Capital expenditures, 9. Board size (Board_SZ), 10. CEO duality (CEO_DualityD), 11. Board tenure (LN_Board_Tenure), 12. Executives compensation (LN_Executives_Compensation), 13. Audit committee independence (Audit_Comm_Independence), 14. Environment management training dummy (Env_Mgt_TrainingD, 15. Board gender diversity (Board_Gen_Div), and 16. Gross domestic product (GDP). Source: own calculation tenure suggested that these factors may influence sustainability decisions. A deeper analysis of the correlations revealed that higher levels of profitability (as indicated by ROA and ROE) were positively correlated with support for climate action initiatives.

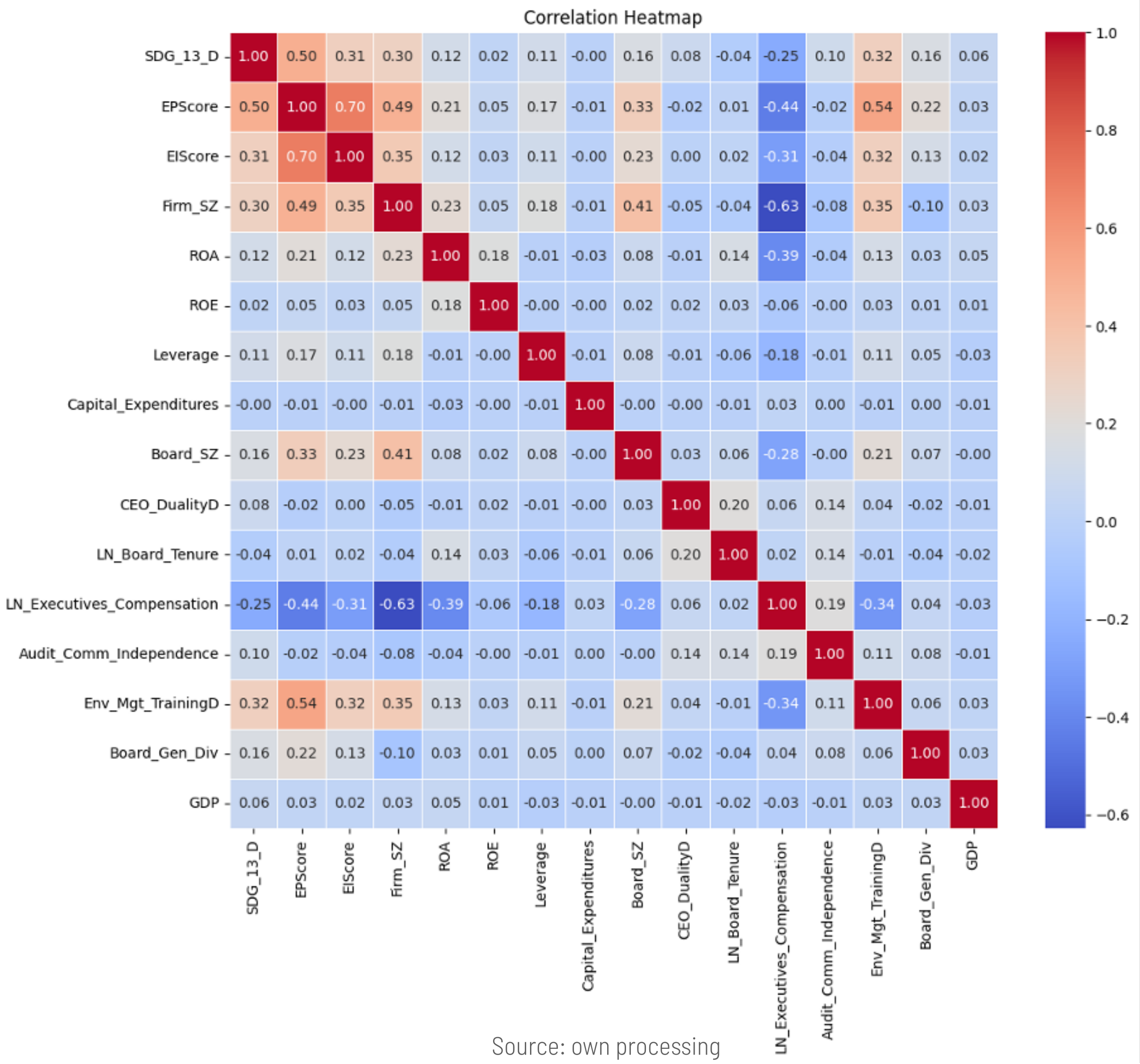
Notably, the presence of structured environmental management training not only supported but also strengthened this relationship, suggesting that investment in such training can enhance the effectiveness of sustainability efforts.

However, the relationship between sustainability performance and financial performance is not straightforward and exhibits a non-linear pattern. While environmental, social, and governance (ESG) factors generally promote better financial outcomes, the impact varies and shows both positive and negative effects depending on the specific context and metrics used, as evidenced in the existing literature (Basuony et al., 2023; Erekson et al., 2008). These findings underscored the complexity of integrating sustainability into corporate strategies they also highlighted the potential for structured environmental management training to enhance corporate commitment to sustainability, thereby suggesting a path for companies to strengthen their support for SDG 13 through improved financial health and targeted management practices.

Correlation matrix

In the correlation analysis, the relationships between several firm-specific variables and their impact on Sustainable Development Goal 13 (Climate Action) were examined. The study extensively analyzed both financial and non-financial metrics, including environmental performance score (EPScore), environmental impact score (EIScore), firm size (Firm_SZ), return on assets (ROA), return on equity (ROE), leverage, capital expenditures, board size (Board_SZ), CEO duality (CEO_DualityD), board tenure (LN_Board_Tenure), executives compensation (LN_Executives_Compensation), audit committee independence (Audit_Comm_Independence), environmental management training (Env_Mgt_TrainingD), board gender diversity (Board_Gen_Div), and gross domestic product (GDP). The primary focus was on the binary variable 'SDG_13_D', which indicated whether a company is making significantly contribution to the achievement of SDG 13.

Figure 1: Correlation heatmap of the factors studied



Source: own processing

The analysis revealed that profitability measures such as ROA and ROE were positively correlated with SDG 13, with correlation coefficients of 0.18 and 0.12, respectively. This suggested that more profitable companies are potentially better positioned to engage in environmentally beneficial practices. Conversely, leverage and CEO duality were negatively correlated with SDG13, with correlation coefficients of -0.01 and -0.02, respectively. These figures indicated governance challenges in achieving climate goals. However, board size showed a significant positive correlation of 0.28 with SDG13, suggesting that a larger board may support more significant commitment to sustainability.

A notable finding from the present study was the strong positive correlation of environmental management training with SDG 13 (0.32). This highlighted the critical role of targeted training in improving a company's climate action initiatives. In addition, environmental performance and impact scores showed strong positive correlations with SDG 13, with correlation coefficients of 0.50 and 0.31, respectively, indicating that firms with higher environmental scores are more aligned with SDG 13 goals. Moreover, board gender diversity maintained a positive correlation of 0.07 with SDG 13, reinforcing the positive impact of diverse governance structures on environmental strategies.

These findings deepen our understanding of the complex interplay between corporate operations, financial performance, and governance attributes such as environmental training and diversity, that influence a company's contribution to climate action. This comprehensive analysis not only expands our knowledge base but also provides a solid foundation for further research into specific strategies that could enhance a company's sustainability impact. Furthermore, the findings informed policy recommendations to optimize corporate governance structures to support broader sustainability efforts.

Application of machine learning methods

Before moderation

Study evaluated the performance of four different machine learning classifiers -decision tree, random forest, gradient boosting, and logistic regression - on a dataset to explore the interplay between corporate profitability and Sustainable Development Goal 13 (Climate Action). The decision tree and random forest models exhibited exceptionally high R2 values of 0.719 and 0.802, respectively, along with perfect precision, recall, and F1-scores of 1.0 for both classes, suggesting a potential overfitting problem due to their ability to capture complex patterns and noise in the training data (Tab. 2).

In contrast, the gradient boosting model, with an R2 of 0.784, and the logistic regression model, with an R2 of 0.751, had more balanced precision and recall scores, indicating a more generalized performance. Specifically, the gradient boosting model achieved precision scores of 0.83 and 0.71 for the negative and positive classes, respectively, with recall scores reflecting this trend at 0.87 and 0.63. Logistic regression, as the linear model in the set, showed the lowest precision and recall scores, suggesting a struggle to capture the more complex nonlinear relationships within the dataset.

These results underscored the importance of model selection in predictive analytics, where the choice between model complexity and generalizability must be carefully balanced to ensure robust predictions that are practical for use in real-world scenarios. Furthermore, the variation in feature importance across models highlighted the need for careful feature engineering and selection to improve model interpretability and effectiveness in predicting SDG-related outcomes.

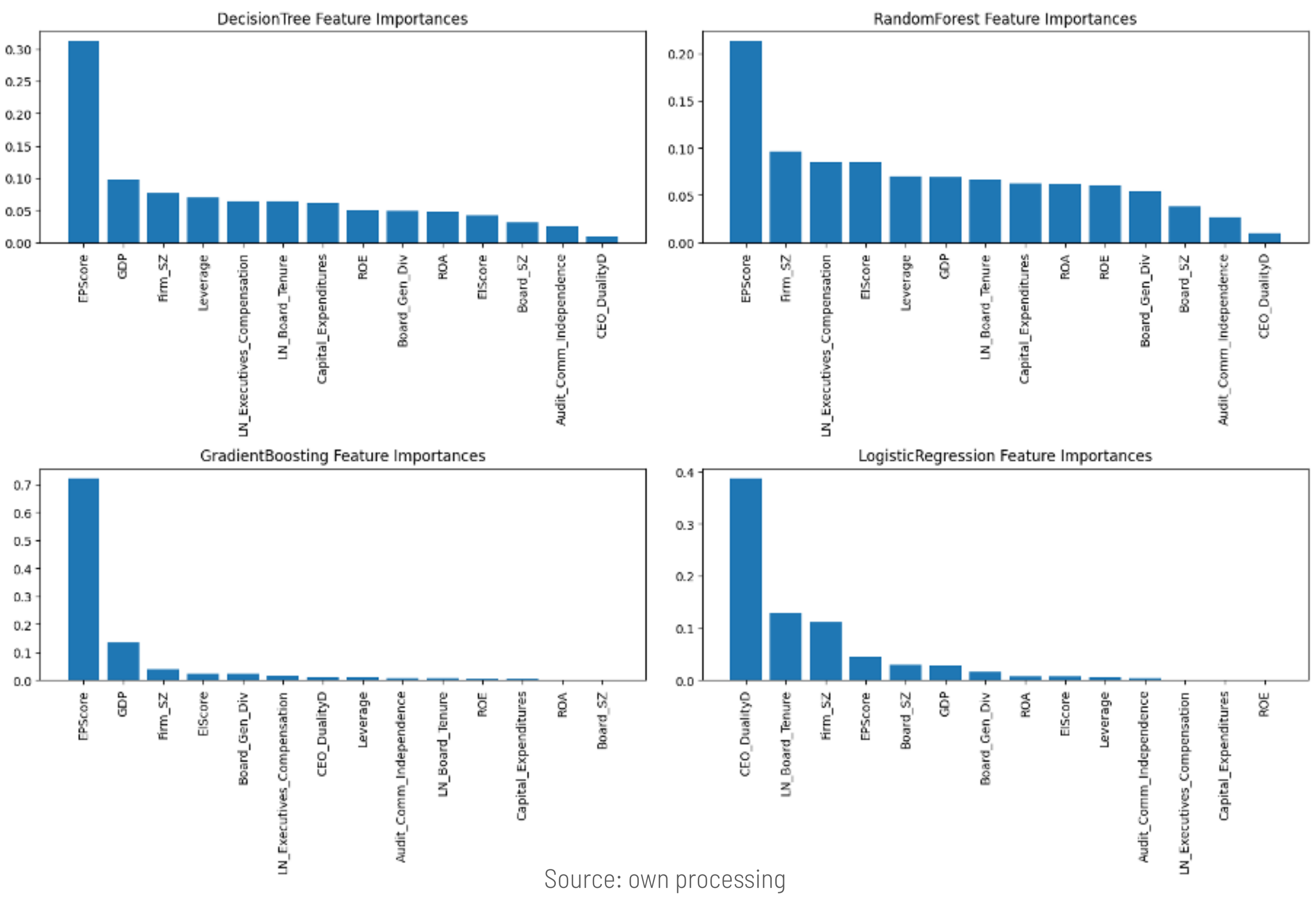
Figure 2 illustrates the importance of features in four machine learning models: decision tree, random forest, gradient boosting, and logistic regression. In the analysis, authors used these models to assess the predictors influencing companies' alignment with Sustainable Development Goal 13 (Climate Action). Each model highlighted different levels of importance of the features, providing insight into the complex interplay between corporate practices and sustainability outcomes.

Table 2: Performance evaluation of the proposed predictive models

Metric	Class	Decision tree	Random forest	Gradient boosting	Logistic regression
Precision	0	1	1	0.83	0.79
	1	1	1	0.71	0.64
Recall	0	1	1	0.87	0.85
	1	1	1	0.63	0.55
F1-Score	0	1	1	0.85	0.82
	1	1	1	0.66	0.59
Support	0	21036	21036	21036	21036
	1	10310	10310	10310	10310
Model accuracy					
R-squared		0.719	0.802	0.784	0.751

Source: Author's Calculation

Figure 2: Feature importance of the selected models



Source: own processing

The decision tree model showed that the environmental performance score (EPScore) was the most significant predictor of SDG 13 alignment, highlighting the central role of environmental practices in corporate sustainability efforts. Firm size (Firm_SZ) and leverage also emerged as important factors, suggesting that larger firms and those with higher leverage may be more engaged in or affected by SDG 13-related activities.

Random forest analyses distributed importance more evenly across several characteristics, including EP Score, ROE, and GDP. This model captured a broader range of influences, from environmental performance to financial health and macroeconomic conditions, reflecting the multifaceted impact of these variables on sustainability initiatives.

Gradient boosting presented a strong contrast, with EPScore dominating the importance of the features, overwhelming other variables. This dominance pointed to the potential of environmental performance metrics as primary drivers for SDG 13 engagement but also raises concerns about overfitting and the need for model calibration.

Finally, the logistic regression model provided a balanced perspective, acknowledging the importance of EPScore and firm size, similar to the decision tree, but also highlighting GDP and ROE as influential predictors. This linear approach suggested a nuanced interdependence between economic factors and corporate sustainability practices, consistent with broader economic trends and financial performance metrics.

After moderation

After introducing moderating variables associated with management training on environmental practices, the authors reassessed the performance of the four machine learning classifiers -decision tree, random forest, gradient boosting, and logistic regression- on the dataset focused on the intersection of corporate profitability and SDG 13 (Climate Action). Adding these moderating variables resulted in subtle yet insightful shifts in model performance metrics.

The decision tree model showed a slight improvement in R2 from 0.719 to 0.722, suggesting a minimal but positive impact of the moderating variables on the model's ability to explain variance (Tab. 3). The random forest model experienced a slight decrease in R2, moving from 0.802 to 0.800, which may indicate a slight overfitting in the pre-moderation model that was corrected by the added complexity. The gradient boosting model remained unchanged in R2, as both values were 0.784. Finally, the logistic regression model showed a slight decrease in R2, from 0.751 to 0.749.

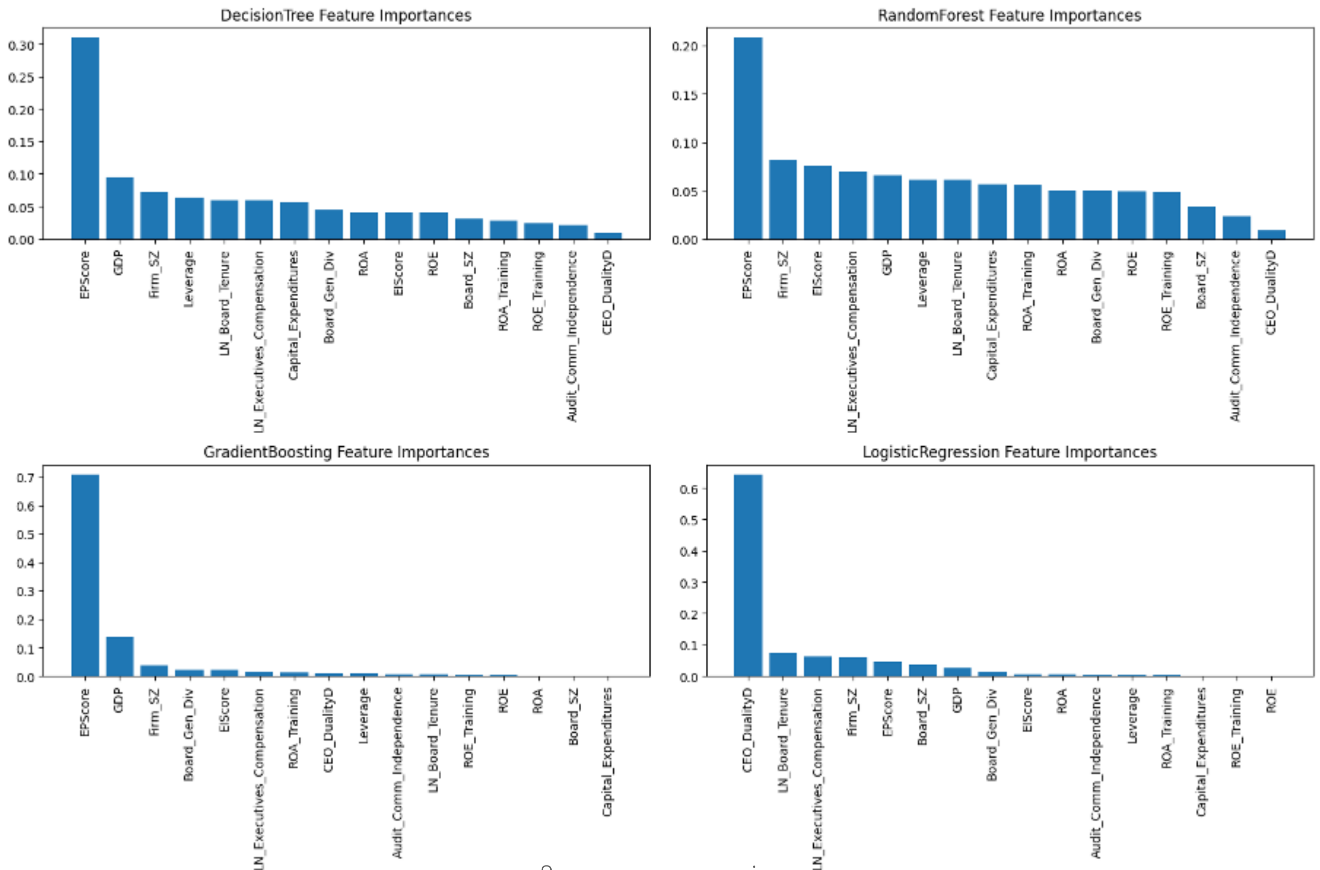
Regarding precision, recall, and F1-score, both decision tree and random forest models maintained perfect scores across both classes, confirming their robustness in classification accuracy, albeit with potential overfitting concerns. Gradient boosting and logistic regression showed

Table 3: Performance evaluation of the proposed predictive models-1

Metric	Class	Decision tree	Random forest	Gradient boosting	Logistic regression
Precision	0	1	1	0.83	0.79
	1	1	1	0.71	0.64
Recall	0	1	1	0.87	0.85
	1	1	1	0.63	0.54
F1-Score	0	1	1	0.85	0.82
	1	1	1	0.67	0.58
Support	0	21036	21036	21036	21036
	1	10310	10310	10310	10310
Model accuracy					
R-squared		0.722	0.722	0.722	0.722

Source: Author's Calculation

Figure 3: Feature importance of the selected models after Moderation



Source: own processing

no significant change in precision and recall, consistently performing below the tree-based models, underscoring their challenges in dealing with complex nonlinear relationships and their excellent resistance to overfitting (table 3).

The introduction of moderating variables resulted in slight changes in the overall metrics, suggesting that the added complexity may have slightly significantly altered the underlying dynamics captured by the models. The stability of the gradient boosting model's performance before and after the introduction of moderating variables indicated its effectiveness in capturing essential features without being heavily influenced by the added interactions. In contrast, the slight changes observed in the logistic regression model performance may indicate its sensitivity to feature space expansion, which affected its ability to generalize.

These findings illustrated the nuanced impact of including environmental management training as a moderating factor in models designed to predict corporate performance relative to climate action goals. While including these variables did not drastically change model performance, it did provide a deeper understanding of how additional data dimensions can subtly influence predictive accuracy and model stability. For policymakers and corporate strategists, these findings underscored the importance of tailored feature selection and model tuning in developing robust predictive tools to inform sustainable business practices aligned with global climate action goals.

Figure 3 shows the feature importance of each machine learning model after introducing moderating variables related to management training on environmental practices. The analysis revealed subtle but insightful shifts in the four models -decision tree, random forest, gradient boosting, and logistic regression designed to explore how management training influences the models' predictions of corporate alignment with Sustainable Development Goal 13 (Climate Action).

In the decision tree and random forest models, there was a slight adjustment in the distribution of feature importance. The environmental performance score (EPScore) had a reduced role, suggesting a redistribution towards features such as firm size and GDP. This shift suggested a nuanced sensitivity of these models to a broader corporate and economic context, potentially enhancing their ability to integrate diverse inputs in predicting sustainability outcomes.

Conversely, the gradient boosting model maintained remarkable stability in its feature importance distribution, with EPScore continuing to dominate. This persistence suggests that despite the new moderating variables, the core predictive power of the Gradient Boosting model remains strongly linked to environmental performance metrics, indicating resistance to shifts in feature weighting caused by new variables.

The logistic regression model showed the most significant changes, with a significant reduction in the dominance of EPScore and an increase in the importance of firm size and GDP. This shift underscored the model's adaptability and increased sensitivity to the economic dimensions introduced by the moderating variables, reflecting a move towards a more balanced approach to the weighting of different predictors.

Comparatively, prior to the introduction of moderating variables, EPScore was the dominant feature in most models, particularly dominant in the gradient boosting model. However, after moderation, there was a clear trend towards a more balanced distribution of feature importance across all models. This redistribution was particularly evident in the logistic regression model, which now placed greater emphasis on broader economic and firm-specific factors.

The adjustments in feature importance due to moderating variables highlighted the complex interplay between environmental management training and other firm characteristics in shaping sustainability practices. While EPScore remains a significant predictor, the increased role of economic and financial features such as GDP and ROE highlighted the broader contextual factors that now play a more prominent role in the models' predictions. This nuanced understanding is critical to the development of more effective predictive tools and strategies that can better capture the multiple influences on corporate sustainability, thereby helping policymakers and strategists design more targeted and effective sustainability initiatives.

DISCUSSION

Analysis of an extensive dataset of 31,346 firms provide critical insights into the relationship between corporate sustainability efforts and financial performance, governance structures, and environmental management practices. These findings contribute to the growing literature on corporate sustainability practices and provided a nuanced perspective on the effectiveness of these initiatives.

The results indicated a modest average level of support for Sustainable Development Goal 13 (Climate Action), with only about one-third of companies actively engaged in related sustainability efforts. This observation was consistent with the findings of Onesti & Palumbo (2023), who found that despite a growing global emphasis on environmental sustainability, practical levels of engagement remain uneven, with many firms still in the early stages of integrating these goals into their core operations. Furthermore, the positive correlation between profitability metrics (ROA and ROE) and support for climate action initiatives was aligned with the conclusions of Martínez-Ferrero & García-Meca (2020), who found that firms with more robust financial performance are often better positioned to invest in sustainable practices due to greater resource availability. This relationship highlighted the importance of financial health as a facilitator of sustainability initiatives, a notion supported by Bhat (2023), who argued that robust corporate governance mechanisms are essential for achieving sustainability goals.

In terms of governance, the data showed that larger board sizes are correlated with a greater commitment to sustainability (correlation coefficient of 0.28 with SDG 13). This finding supported the claims of Ikram et al. (2020) and Bhat (2023), who argued that larger governance bodies can provide diverse perspectives and resources, thereby enhancing a firm's ability to implement effective sustainability strategies. However, the observed modest negative correlations for leverage and CEO duality with SDG 13 highlighted the challenges of governance in achieving climate action goals, suggesting that firms with high leverage or CEO duality may encounter conflicts or resource constraints that hinder their sustainability efforts. This finding was consistent with the theoretical framework proposed by Wang et al. (2023), who argued that governance structures significantly influence the implementation of environmental strategies.

Notably, the present study found a strong positive correlation between environmental management training with SDG 13 (correlation coefficient: 0.32). This suggested that targeted training programs can significantly enhance firms' capabilities to pursue climate action, supporting the theoretical model proposed by Alkan & Kamaşak (2023), which emphasized the role of internal capability building in promoting sustainability. Moreover, the correlation analysis revealed strong positive correlations between environmental performance and impact scores with SDG 13, suggesting that firms with higher environmental scores align their operations with broader sustainability goals. This observation was consistent with the findings of Maneenop (2023), who highlighted a similar pattern across firms.

In the context of the machine learning analysis, the variation in model performance before and after the introduction of moderating variables was indicative of the complexity of predicting sustainability outcomes. Decision trees and random forests exhibited potential overfitting, a common problem also identified by Zhao et al., (2018). Lim & Park (2022) in their analysis of environmental data. The gradient boosting and logistic regression models, which demonstrated more generalizable performance, underscored the findings of Lee (2012) and Gaidarenko et al. (2022) that simpler models can sometimes provide more reliable insights in complex datasets characterized by nonlinear relationships and interactions. The subtle changes observed after introducing moderating variables into the predictive models provided empirical support for the theoretical proposition that additional dimensions in the data can improve the model's ability to capture the underlying dynamics, however the effect may not always be drastic. Overall, these findings underscored the complex relationship between corporate sustainability efforts and various financial and governance factors, enriching our understanding and extending the discussion in the current literature on corporate sustainability.

CONCLUSION

This research has systematically explored the complex dynamics between corporate profitability, SDG 13 Climate Action, and the moderating effects of environmental management training and teams. The comprehensive analysis, using advanced machine learning techniques, has uncovered important insights that significantly expand our understanding of the link between firm financial performance and environmental sustainability initiatives.

The findings confirmed a robust positive correlation between corporate profitability and support for SDG 13 Climate Action. More specifically, firms with higher profitability tend to demonstrate more significant commitment and effectiveness in implementing initiatives aligned with the Climate Action goals. This relationship underscores the potential for financial resources freed up by higher profits to be channeled into sustainable practices that are both environmentally beneficial and supportive of broader sustainability goals.

Critically, the results showed that the presence and quality of environmental management training and teams significantly strengthen this relationship. Companies with structured environmental management practices not only engage more deeply in sustainability efforts but also leverage these practices to improve financial performance and strategic positioning in the marketplace. This dual benefit acts as a catalyst, fostering a cycle of sustainability that contributes to continuous improvement in both environmental and financial performance.

Using machine learning models has provided more profound insights into the complex and nonlinear interactions among the variables studied. The predictive models used in this study, specifically decision trees, random forests, gradient boosting, and logistic regression, have demonstrated varying degrees of effectiveness in capturing and interpreting these interactions. These analytical advances have allowed for a more nuanced understanding of how environmental management training and teams function as critical levers in enhancing a company's commitment to SDG 13.

These findings have profound implications for both business leaders and policymakers. For businesses, the clear message is that integrating robust environmental strategies and training programs into corporate governance and operational frameworks is not only a moral imperative but also a strategic one that enhances profitability and sustainability. For policymakers, the study highlighted the importance of creating a supportive regulatory environment that encourages firms to adopt sustainable practices through incentives and training programs.

This study has some limitations. The reliance on machine learning models may introduce biases due to data availability and quality, affecting generalizability. It primarily establishes correlations rather than causation, requiring further research for validation. Additionally, unobserved factors like regulatory differences and cultural variations may influence the findings. Future studies should explore diverse datasets and alternative modeling approaches.

In conclusion, this research contributed valuable empirical evidence to the discourse on the synergy between financial performance and environmental sustainability. It provided a roadmap for firms seeking to integrate sustainable practices into their core operations and for governments seeking to foster a regulatory environment conducive to sustainable business growth. This research not only enriched the academic literature on corporate sustainability but also served as a pragmatic guide for continuous improvement in corporate and environmental governance.

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