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# The Effects of Renewable Energy Consumption on Financial Performance: An Explainable Artificial Intelligence (XAI)-Based Research on the BIST Sustainability Index

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**ABSTRACT**

The main purpose of this study is to analyze the relation between renewable energy consumption and the financial performance of businesses included in the Borsa Istanbul (BIST) Sustainability Index using the Explainable Artificial Intelligence (XAI) method and to evaluate its predictability using machine learning methods. Within the scope of this research, annual business data from 2021 to 2023 are used. In this context, this study compared the forecast performances of different machine learning (ML) methods (XGBoost, Random Forest, and LightGBM) by analyzing them using SHAP (SHapley Additive Explanations), an XAI method. Some variables in this study consist of non-financial indicators, while the others consist of financial accounting and market-based indicators. The results show that renewable energy consumption has a very limited negative effect on ROA, whereas an increase in the total renewable energy ratio provides a positive contribution to ROA, albeit at a low level. Renewable energy consumption has a low positive effect on ROE. The XGBoost for ROA and Random Forest algorithm for ROE were more successful in estimation. This study goes beyond traditional statistical analyses and reveals the financial effects of accounting indicators in detail using XAI-based methods and contributes to enterprises' decision-making processes regarding energy transformation.

**Keywords:** Renewable Energy Consumption, Financial Accounting, Financial Performance, BIST Sustainability Index, machine learning, Explainable Artificial Intelligence
**JEL Classifications:** C45, M21, M41, Q56

## 1. INTRODUCTION

The use of energy resources (ER) is one of the main factors affecting economic, social, and environmental changes around the world. In the literature, ER are categorized as renewable energy (RE) and non-renewable energy resources according to the use of ER (Rybár et al., 2015; Yıldırım et al., 2024). Renewable energy sources (RES) include solar, wind, bioenergy, et al., which can progress environmental quality by reducing greenhouse gas emissions (Sitompul et al., 2024). Non-RES are divided into two types: fossil-based energies (oil, gas, coal) and nuclear-based energies (Yıldırım et al., 2024). Furthermore, increasing awareness with the usage of RES in the world, lately events have also prompted initiatives to expand their use (Dopierała et al., 2022). The use of RES for producing energy is becoming an integral part of climate change and energy policy globally (Morina et al., 2021). It is known that climate change is mainly caused by the rise in greenhouse gas emissions from the combustion of fossil fuels (Atif et al., 2021). Recent data show that more than 75% of global greenhouse gas emissions come from fossil fuels (United Nations, n.d.). Research has emphasized the pressing need to switch from fossil fuels to RES in order to lower greenhouse gas emissions and lessen the effects of climate change (Uyar et al., 2024). With regard to the 2025 World Energy Report of the International Energy

Agency (IEA), important steps have been taken in the wake of zero emissions by 2050 to protect against the negative impacts of climate change, and targets have been set for passing to RE in the place of fossil fuels (IEA, 2021). Nowadays, many companies are enhancing their usage of RE to reach sustainable development goals (Hulshof and Mulder, 2020). The widespread use of RES provides for the conservation of natural resources and is agreed to be a significant tool in order to promoting sustainable development (Xu and Liu, 2019). Sustainable development has three aspects: economic, social, and environmental. It also helps businesses in these areas (Shin et al., 2018). As a result, an energy transition should be provided to facilitate the change of non-RES with RES in order to ensure that the sustainability goals of businesses are realized (Hassan, 2019).

Accounting literature draws attention to growing sustainability concerns (Christensen and Himme, 2017). In this context, energy management strategies are an important area of discussion (Gray, 2010). Considering companies' significant contribution to energy consumption and greenhouse gas emissions, it is important to implement effective energy efficiency policies and increase the use of green energy (Uyar et al., 2024). Energy management systems can perform a crucial role in order to monitor energy consumption and reduce energy-related costs (and sustain these savings over time) (Van Gorp, 2015). While the use of RE enables businesses to create an environmentally sensitive image, it can also increase their reputation and strengthen their position in the market. This situation offers businesses a competitive advantage and increases sales. In this context, the transition of enterprises to RE provides not only environmental but also economic and social benefits (Manta et al., 2025; Sitompul et al., 2024). On the other hand, accounting provides an advantage to businesses by measuring and analyzing the financial impacts of sustainable development (Hassan, 2019). Today, business managers are becoming increasingly sensitive to making decisions that are influenced by the social and environmental aspects of the business (Schaltegger and Zvezdov, 2015). In particular, financial analyses enable a clearer assessment of business profitability, liquidity, financial structure, and growth performance using accounting data. Financial data have become a determining factor in enterprises' future energy transformation decisions. In summary, accounting plays a critical role in measuring, analyzing, and reporting the relationship between sustainable energy management and financial performance, contributing to the evaluation of the financial impacts of RE use in enterprises and making strategic decisions (Christensen and Himme, 2017; Gray, 2010).

Developed and developing countries use different tools and strategies to achieve economic growth and financial development (Yang et al., 2024). The use of RE has been proven to improve the sustainable performance of businesses (Kholaif et al., 2022). However, although the use of RE for businesses can be viewed as a means of improving environmental performance, it is still a basic question whether it pays off economically (Ruggiero and Lehkonen, 2017). Whether it is profitable to be green is still among the issues that remain to be resolved (Shin et al., 2018). Sitompul et al. (2024) have suggested that the adoption of RE can cause long-term cost advantages, particularly for energy-intensive sectors, which can favorably affect businesses' profitability.

Due to environmental challenges, climate change is now being analyzed from a financial perspective (Ekwueme et al., 2021). The literature increasingly supports that businesses that invest in the RE have an advantage in terms of long-term financial profitability (Atif et al., 2021; Hulshof and Mulder, 2020). However, there is no clear consensus in the literature on the impact of Renewable Energy Consumption (REC) on enterprises' financial performance. In addition, most previous studies in this area have been based on traditional statistical analyses, and the use of Explainable Artificial Intelligence (XAI)-based methods is limited. In this context, the fundamental objective of this study is to analyze the relation between the REC and the financial performance of enterprises in the Borsa Istanbul (BIST) Sustainability Index using the XAI method and to evaluate its predictability using machine learning methods. Within the scope of this research, annual data of the enterprises for the period 2021-2023 were used. The non-financial data of the enterprise were obtained from the Sustainability Reports, Annual Reports, and Integrated Reports; financial accounting data were obtained through Finnet2000plus. In this context, in this study, the prediction performances of different machine learning methods (XGBoost, Random Forest, and LightGBM) were compared by analyzing SHapley Additive Explanations (SHAP), which is an XAI method. Some of the variables in this study consist of non-financial indicators, while others consist of both financial accounting indicators and market-based performance indicators. Within the scope of the research, answers to the following basic questions will be sought:

1. How does the REC of companies listed on the BIST Sustainability Index affect their financial accounting performance, such as their ROA and ROE?
2. How do XAI methods provide an advantage when analyzing financial performance?
3. How do XGBoost, Random Forest, and LightGBM models perform in terms of financial performance prediction, and which are the most successful machine learning methods?

This study aims to fill this gap in literature by integrating XAI methods with financial accounting analyses. In particular, comparing the prediction performance of different machine learning methods provides a more in-depth examination of the impact of REC on financial accounting indicators. Although traditional statistical methods are generally used in literature, this study increases interpretability by making the decision processes of the model transparent using XAI techniques. By going beyond traditional accounting approaches, the financial impacts of REC are analyzed in a more comprehensive framework. Accordingly, this study helps businesses make more informed and strategic decisions during the transition to RE. The study consists of 5 chapters. The study is summarized in the introduction section and reveals its originality. Then, previous studies were analyzed by literature review. In the methodology section, information about the dataset and variables used in this study is provided, and the XAI and SHAP methods and machine learning methods are explained. Finally, the study was concluded by answering the research questions in line with the obtained findings.

## 2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

In recent years, ongoing environmental problems (e.g. global warming, natural disasters) around the world have attracted more and more attention. This has demonstrated that climate change is not only an environmental issue but also an economic and financial one (Ekwueme et al., 2021). In other words, companies, investors, and economists are now beginning to consider climate change in terms of financial performance. For example, issues such as how climate change may affect companies' financial positions and whether it creates investment risks are discussed. A review of the literature in Turkey reveals a limited number of studies on REC and financial performance. However, the literature has revealed different results regarding the impact of RE on corporate profitability and financial performance. In this context, some studies have suggested that the use of RE can increase financial performance, while others have suggested that it does not. Accordingly, in this part of the study, studies on the effects of REC on financial performance are analyzed.

Some studies have suggested that investments in RE increase financial performance. Atif et al. (2021) stated that since female managers are more likely to advocate the use of RE, it can increase financial performance. Therefore, the study shows that gender diversity positively impacts the use of RE. Westerman et al. (2020) showed that RE companies have higher profitability than traditional energy companies. Because it shows that RE can increase profitability by improving energy efficiency, decreasing operational costs, and increasing reputation. Shin et al. (2018) argued that the use of RE can enable firms to increase cash flows and profitability. It is in the direction that businesses can provide a competitive advantage by improving relations with customers and thus increase their market share by announcing the use of RE. Morina et al. (2021), in a study on RE firms, concluded that RE policies increase profitability in the long term but not in the short term. Hassan (2019) proved that the effects of RE incentive policies on enterprises' financial performance improve the OECD countries' energy companies' financial performance.

Another part of the studies is that there is no sensitivity to RE if there is no win-win situation in businesses (Hulshof and Mulder, 2020). Hulshof and Mulder (2020) also argued that RE has no impact on profit. They stated that businesses can invest in RE when it directly contributes to their profit targets. Another study suggested that the adoption of RE only improves environmental performance without any economic benefits (Ruggiero and Lehkonen, 2017). Ruggiero and Lehkonen (2017) concluded that the use of RE negatively affects business performance and negatively affects long-term performance. They stated that this finding can be explained by the combined impact of overcapacity and low energy demand in developed countries. Włodarczyk et al. (2024) argued that an increase in the renewable energy ratio in the production structure can importantly reduce the profitability of companies. The comparatively high expenses linked to the development of RE and the evolving legislative framework surrounding such investments provide one explanation for this.

Another view in the literature is also that traditional energy and RE have similar financial results. In this regard, Dopierała et al. (2022) provided evidence that the financial performance of renewable energy producers is not markedly different from that of conventional energy producers. Martí-Ballester (2017) argued that the usage of RE does not dramatically impact corporate financial performance.

## 3. METHODOLOGY AND DATA

In the method section of the study, how the dataset was created was first mentioned, and the target and input variables were explained. Then, information about the XAI and SHAP methods was provided, and the XGBoost, Random Forest, and LightGBM algorithms from the machine learning methods were included.

### 3.1. Dataset

In this study, the impact of the renewable energy consumption of companies included in the BIST Sustainability Index on financial performance was analyzed using SHAP, one of the XAI methods. The study included 84 companies listed in the BIST Sustainability Index published by the Public Disclosure Platform in October 2024. To access data on energy consumption, the Sustainability Report, Activity Report, and Integrated Reports on each company's website were examined one by one. However, only 32 companies' renewable energy consumption data could be accessed, and the remaining companies were excluded from the scope of the research. Annual data for the years 2021-2023 were analyzed in the study. BIST company codes are presented in Table 1.

The BIST Sustainability Index is a financial index that brings together businesses with high sustainability performance. The reason for choosing this index is that it provides a platform where companies operating in accordance with sustainability rules in Turkey can evaluate their environmental performance. In addition, the fact that it includes financial and non-financial information on energy use has also been effective in its choice.

Financial indicator data were obtained from the Finnet2000Plus database. In the literature, various accounting-based financial indicators (such as ROA, ROE, Debt to Assets Ratio, Debt to Equity Ratio) are often used to represent the financial performance of businesses (Bergmann et al., 2017; Fan et al., 2017; Hu, 2024; Hulshof and Mulder, 2020; Morina et al., 2021; Simionescu et al., 2020) and market-based indicators (e.g., Price to Book Value, Earnings Per Share, and Firm Size) (Dopierała et al., 2022; Hu, 2024; Simionescu et al., 2020).

In the study, SHAP analysis, one of the XAI methods that explains the decision processes of machine learning methods and deep

**Table 1. BIST codes of the companies used in the study**

| BIST Codes | | | | | |
|---|---|---|---|---|---|
| AGESA | ARCLK | DOHOL | LOGO | TKFEN | VESBE |
| AKCNS | AYGAZ | DOAS | MAVI | THYAO | VESTL |
| AKENR | BIMAS | FROTO | MGROS | TTRAK | |
| AKGRT | BIZIM | GWIND | NUHCM | SISE | |
| ALBRK | BRISA | KERVT | OTKAR | VAKBN | |
| ANHYT | CIMSA | KCHOL | SASA | ULKER | |

learning models, was used. The analyses were performed using the "Python" programming language. The variables used in the study are presented in detail in Table 2.

The target and input variables are given in Table 2. In the study, the financial performance of the companies, ROA and ROE, which are accounting-based performance measures, was taken as target variables. The independent variables are REC, TEC, RER, D/A, D/E, TAG, TEG, PB, EPS, and FS, respectively.

## 3.2. Explainable Artificial Intelligence (XAI)

ML methods use historical data to produce a prediction result without providing details about the relationships between the data (Karamanou et al., 2022). This is referred to as a "black box." XAI was developed to help produce transparent models to explain how black boxes make decisions. Especially in machine learning, there is often a trade-off between accuracy and interpretability (Adadi and Berrada, 2018). The goal of the XAI program is to create explainable models that allow users to understand and manage AI systems. The program aims to enable end users to understand the decisions of AI systems, understand the logic of the system, and appropriately trust it. XAI explanations show the strengths and weaknesses of the system, help predict future behavior and allow users to correct errors. This allows complex AI technologies to become more transparent and understandable (Gunning and Aha, 2019).

XAI research is fundamentally shaped around two main approaches: the development of directly interpretable predictive models (Hind et al., 2019) and the creation of model-independent explanation frameworks to increase the understandability of existing predictive models (Dieber and Kirrane, 2022; Karamanou et al., 2022; Plumb et al., 2018). Among the approaches that fall into the second group, powerful XAI methods such as LIME, Anchors, XGNN, and SHAP stand out (Holzinger et al., 2022)

## 3.3. SHapley Additive exPlanations (SHAP)

SHAP is a unified framework proposed in 2017, developed by Lundberg and Lee to help interpret the predictions of complex models such as machine learning and deep learning(Lundberg and Lee, 2017). The SHAP technique is one of the important XAI methods used to understand and interpret the prediction processes of complex machine learning methods. This technique helps to determine the importance of variables in the model and to evaluate the reliability of the model (Gunning and Aha, 2019). SHAP makes the decision processes of machine learning and deep learning models transparent based on Shapley values, which are based on game theory. This method is based on the principle of analyzing the score changes that occur when each player is randomly substituted for a specific teammate. Thus, the individual contribution of each player can be measured (D'Amato et al., 2024). However, since each player has to be evaluated individually, the calculation of the Shapley value becomes exponentially complex as the number of players in the team increases. SHAP follows a similar logic and considers the attributes that constitute the inputs of the model instead of the players (Christoph, 2020). Accordingly, SHAP aims to make the decision mechanism of the model more understandable by analyzing the contribution of each feature to the prediction process of the machine learning algorithm. Although SHAP is a model-independent (agnostic) annotation algorithm, there are also optimized versions for specific model types (Yıldırım et al., 2024).

**Table 2: Variables used in the analysis**

| Variable type | Variable description | Source |
|---|---|---|
| Target variables | Return on Assets (ROA)<br>Return on Equity (ROE) | Finnet2000Plus |
| Input variables | Renewable Energy Consumption (MWh) (REC)<br>Total Energy Consumption (MWh) (TEC)<br>Renewable Energy Ratio (RER) (Renewable Energy Consumption/ Total Energy Consumtion) | Sustainability Report, Annual Report, Integrated Report |
| | Debt to Assets Ratio (D/A Ratio)<br>Debt to Equity Ratio (D/E Ratio)<br>Total Asset Growth Rate (TAG)<br>Total Equity Growth Rate (TEG)<br>Pirice to Book Value (PB)<br>Earnings Per Share (EPS)<br>Firm Size (FS) | Finnet2000Plus |

Shapley values provide an average measure of the marginal contribution of each feature in a machine learning model across all possible combinations, revealing the true impact of the feature in prediction (Kar and Bakirarar, 2023; Karamanou et al., 2022).

SHAP equation (1) is as follows (Yıldırım et al., 2024).

$$g\left(z'\right) = \Phi_0 + \sum_{j=1}^{M} \Phi_j z'_j \tag{1}$$

In Equation 1, g is a descriptive model used to explain the decision-making process of the model. M is the maximum number of attributes considered by the model, while $z' \in [0,1]^M$ represents a simplified dataset. This dataset is a simplified version of the original dataset, using a binary notation indicating the presence (1) or absence (0) of certain attributes.

Here, $\Phi_j \in R$ is the SHAPley value that contributes to the model. The SHAPley value, $\Phi_j$ is calculated as in equation (Yıldırım et al., 2024):

$$\Phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{j\}) - f(S)] \tag{2}$$

In the formula $\Phi_j$, the difference in prediction when attribute $j$ is included and excluded from the model is calculated. That is, the marginal contribution of attribute $j$ is found. $F$ represents the set of all attributes used in the model. The expression $S \subseteq F \setminus j$ in the formula indicates the possible subsets when the attribute $j$ is excluded (Yıldırım et al., 2024).

## 3.4. Machine Learning Algorithms

This section summarizes the XGBoost, Random Forest, and LightGBM algorithms used to analyze the dataset. To improve the performance of the predictive models, the GridSearchCV method was used for hyperparameter optimization, and 5-fold cross-validation was applied.

### *3.4.1. Extreme gradient boosting (XGboost)*

XGBoost is a generalized tree boosting (GB) algorithm and is a scalable, end-to-end tree boosting system. It uses strategies such as cache access patterns, data compression, and sharding to build this system. Thanks to these strategies, it can process billions of data while consuming fewer resources. XGBoost can run 10 times faster than other methods, even on a single machine. It also accelerates the learning process and facilitates model discovery owing to its parallel and distributed processing capabilities. It developed a sparsity-aware approach to deal with sparse data and optimized tree learning with weighted quantile sketching (Chen and Guestrin, 2016).

XGBoost prunes trees more efficiently by using quadratic Taylor expansion to optimize the loss function, thus achieving higher accuracy compared to traditional GBM. It also optimizes the learning process until the residual values are minimized through effective tuning of hyperparameters. (Karamanou vd., 2022). To conclude, XGBoost stands out among alternative methods thanks to its capabilities like built-in regularization, advanced pruning techniques, effective handling of missing data, and computational efficiency. Its scalability makes it especially advantageous for processing extensive datasets (Bulut, 2024; Dündar and Koçer, 2024).

### *3.4.2. Random forest (RF)*

The random forest algorithm, introduced by Breiman (2001), has been successfully applied to many classification and regression problems. The algorithm produces a result by averaging and combining the predictions of randomly generated decision trees. It applied a splitting process using a random feature for each node. This has reduced error rates, increased resistance to noise, and made it possible to analyze variable importance (Biau and Scornet, 2016; Breiman, 2001; Bulut, 2024; Schonlau and Zou, 2020).

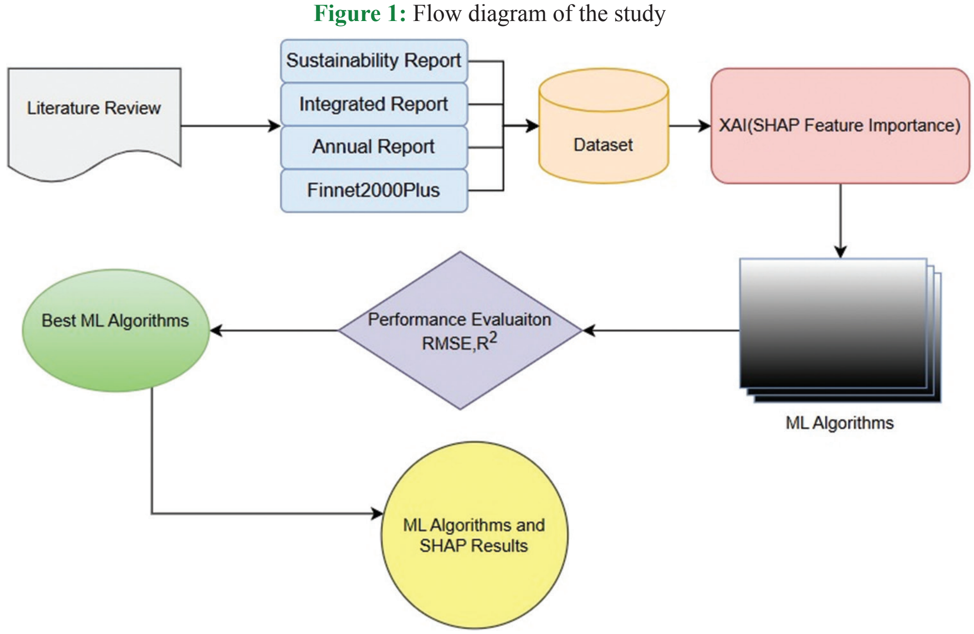
### *3.4.3. LigthGBM*

LightGBM, developed by Microsoft in 2017, is a ML algorithm that aims to make gradient boosting models run faster and more efficiently based on decision trees. While the traditional GBDT and XGBoost algorithms are effective on high-dimensional data sets, their performance on large data volumes is limited. This is because it needs to compute the information gain of all data samples by scanning all possible split points for each feature. As a solution to this problem, LightGBM reduces the size of features by combining them with the Exclusive Feature Bundling (EFB) technique and estimates the information gain with high accuracy by reducing the data size with Gradient Based Unilateral Sampling (GOSS) (Ke et al., 2017). The main goal of LightGBM is to increase scalability and optimize computational efficiency. To achieve this goal, the algorithm uses the GOSS method, which selectively highlights the most informative examples in gradient computations. GOSS significantly reduces training time and memory consumption while at the same time reducing the data size, resulting in faster results (Bulut, 2024). LightGBM also adopts a leaf-based tree growth strategy. This strategy expands the leaf with the best split score at each step so that fewer trees perform better. Using a histogram-based approach, the feature values are divided into small bins, and histograms are constructed over these bins. The histograms are optimized to determine the optimal split points for each leaf. Moreover, the computational cost is reduced as only one leaf's histogram needed to be updated(Hajihosseinlou et al., 2023; Iban, 2022).

## 4. ANALYSIS AND FINDINGS

The flow diagram of the study is presented visually in Figure 1. In line with the purpose of the study, the relevant literature was reviewed, and the conceptual framework was created by determining the variables. A comprehensive data set was created by combining data obtained from sources such as sustainability reports, integration reports, annual reports, and Finnet2000Plus.

**Figure 1:** Flow diagram of the study



ROA and ROE were determined as target variables representing financial performance, and SHAP analysis, one of the XAI methods, was applied to this data set to examine the effects and importance of the variables on the model. Forecasting models were developed using XGBoost, Random Forest, and LightGBM algorithms to predict financial performance (ROA and ROE). To achieve the best performance, hyperparameter optimization was performed using the GridSearchCV method, and 5-fold cross-validation was applied. Finally, the performances of the prediction models are compared, and the most successful model is determined.

### 4.1. SHAP Analysis

In the study, the SHAP feature importance values were calculated to explain the effects of the input variables on ROA and ROE. This process was performed using the SHAP library in the Python programming language. The SHAP feature importance values were obtained through a machine learning algorithm trained with the Random Forest Regressor model. In addition, the Kernel Explainer method was applied to provide a clearer explanation of the model's decision processes.

As seen in Figure 2a and b, Earning Per Share (EPS) has the highest average SHAP value. This shows that EPS is the most effective variable for explaining ROA and ROE forecasting models. Then, the most influential variables for ROA are (a) Debt-to-Equity Ratio, Total Assets Growth Rate, Price to Book Value, Debt to Assets Ratio, and Firm Size, while the variables related to energy consumption have the lowest impact. Renewable Energy Ratio, Total Energy Consumption and Renewable Energy Consumption variables, respectively, were found to be the variables with the lowest effect in the model used to predict ROA.

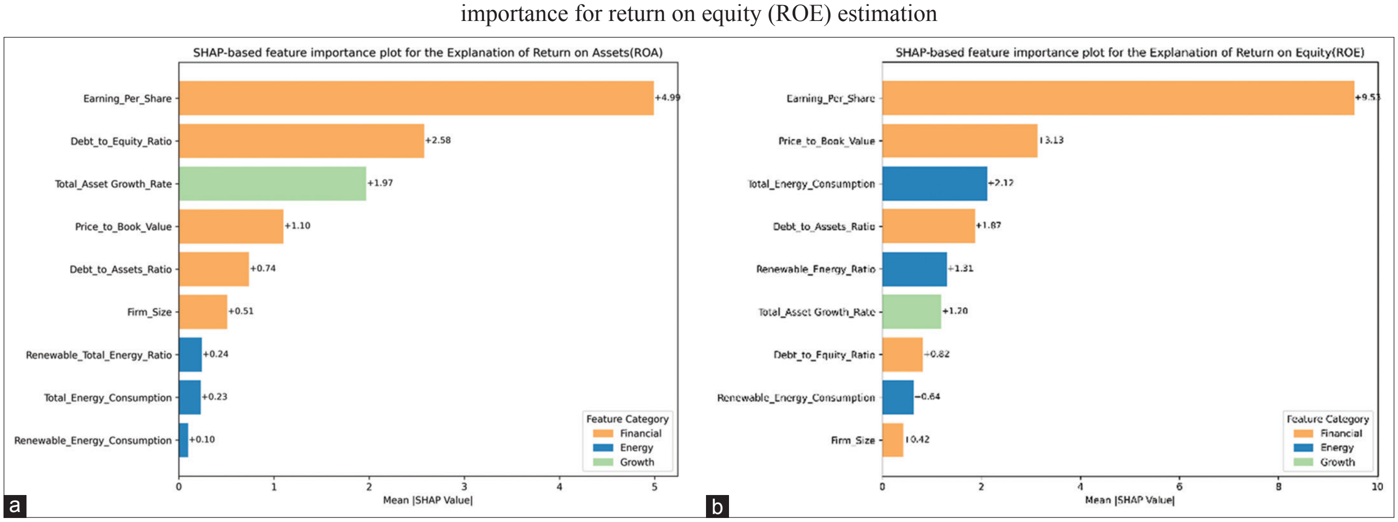
As shown in Figure 2b, Price to Book Value, Total Energy Consumption, Debt to Assets Ratio, Renewable Energy Ratio, Total Assets Growth Rate, Debt to Equity Ratio, Renewable Energy Consumption, and Firm Size are ranked as the most important variables in ROE estimation after EPS, which is the variable with the highest significance value. The ranking shows that Renewable Energy Consumption is the variable with the lowest impact on ROE.

The Waterfall plot in Figure 3 is referred to as local interpretability, which provides an explanation of the predictions for a single sample in the dataset. SHAP describes how individual forecasts are arrived at through contributions from each of the variables given as inputs to the model (Iban, 2022). This produces simple but informative outputs. Figure 3a describes the main contributions of each attribute to the prediction of the median ROA in the dataset. Summing up, all these contributions yields f(x) = 26.5, which is the model's final estimate for the observation of interest. Positive contributions in the graph increase the prediction value. In Figure 3, EPS make the highest contribution to the forecast value with +14.2, followed by the Debt-to-Equity Ratio with +2.10. This indicates that an increase in the profitability of the company has a direct positive impact on ROA. The debt-to-equity ratio also made a significant contribution (+2.1), suggesting that taking advantage of financial leverage can improve asset efficiency. The variable with the largest downward impact on the forecast is the Total Asset Growth Rate variable colored in blue in the graph. The Renewable Energy Consumption, Total Energy Consumption, and Firm Size variables also have a small negative impact on the forecast.

The low negative impact of Total Energy Consumption on ROA may be because energy costs suppress the financial performance of the company. The low but negative effect of Renewable Energy Consumption can be explained by the fact that the initial investment costs of these resources may be high or they are not yet fully optimized.

Figure 3b illustrates the main contributions of each feature to the prediction of the median ROE in the dataset. Summing up all these contributions yields f(x) = 71.63, which is the model's final estimate for the relevant observation. Positive contributions in the graph increase the prediction value. In Figure 3b, EPS makes the highest contribution to the forecast value with +33.38, followed by Price to Book Value +4.1 and Renewable Energy Ratio +3.08. On the other hand, the Total Energy Consumption and Debt-to-Assets-Ratio, which are colored blue in the graph,

**Figure 2:** Feature importance by SHAP. (a) SHAP-based feature importance for return on assets (ROA) estimation, (b) SHAP-based feature importance for return on equity (ROE) estimation



have the largest negative impact on the forecast. The Total Asset Growth Rate, Renewable Energy Consumption, Firm Size, and Debt-to-Equity Ratio variables also had a positive impact on the forecast to a lesser extent.

The results reveal that EPS, Price to Book Value, and the Renewable Energy Ratio are determinants of ROE. In particular, the high positive contribution of the EPS variable indicates that the firm's EPS have a direct and strong effect on ROE.

Figure 4a shows the SHAP beswarm plot showing the distribution of SHAP values for each attribute in predicting ROA and (b) ROE. In this graph, each point represents an observation in the dataset. The SHAP value on the horizontal axis shows the effect of the input variables on the target variable. Low values in the observation are shown in blue, while high values are shown in red. The variables with the highest impact are ordered from top to bottom. As can be seen from both graphs, higher EPS have the strongest positive effect on ROA and ROE.

In Figure 4a, as EPS decreases, its effect on ROA becomes increasingly negative. This shows that there is a strong linear relationship between EPS and ROA. Similarly, there is a high linear relationship between EPS and ROE. Low levels of the Debt to Equity Ratio mostly have a positive effect on ROA, while some low values have negative effects. On the other hand, as the Total Assets Growth rate increases, there is a strong positive effect on ROA estimates. In terms of the Price to Book Ratio, a low book value has a small negative impact on ROA.

Figure 4b shows the distribution of the SHAP values for each attribute to estimate the ROE. EPS stands out as the factor with the largest positive impact on ROE. It is observed that if EPS decreases, its impact on the forecast becomes negative, and there is a strong linear relationship between ROE and EPS. Price to Book Value shows a positive impact on ROE, with lower PB values generally having less positive or negative impact. Total Energy Consumption is among the factors that reduce the forecast value the most, and the suppressive effect of energy consumption on ROE is evident. On the other hand, the Renewable Energy Ratio shows a positive relationship with ROE. Among other characteristics, the Debt to Assets Ratio and Debt to Equity Ratio negatively affect the predictive value, while the Renewable Energy Consumption, Firm Size, and Total Asset Growth rate make less significant but positive contributions.

Based on the findings in Figure 4, the results reveal that Total Energy Consumption is one of the factors with the highest negative impact on ROE. However, it also has a low but negative impact on ROA. ROE has a very low positive effect on Renewable Energy Consumption. While Renewable Energy Consumption has a very limited negative impact on ROA, the increase in the proportion of renewable energy makes a positive contribution to ROA, albeit at a low level.

## 4.2. Comparative Analysis of Machine Learning Methods

This section aims to determine which ML algorithms are the most successful in estimating the target variables. XGBoost, Random

**Figure 3:** Individual prediction explanation waterfall visualization. (a) Individual Prediction Explanation Using SHAP for ROA. (b) Individual Prediction Explanation Using SHAP for ROE

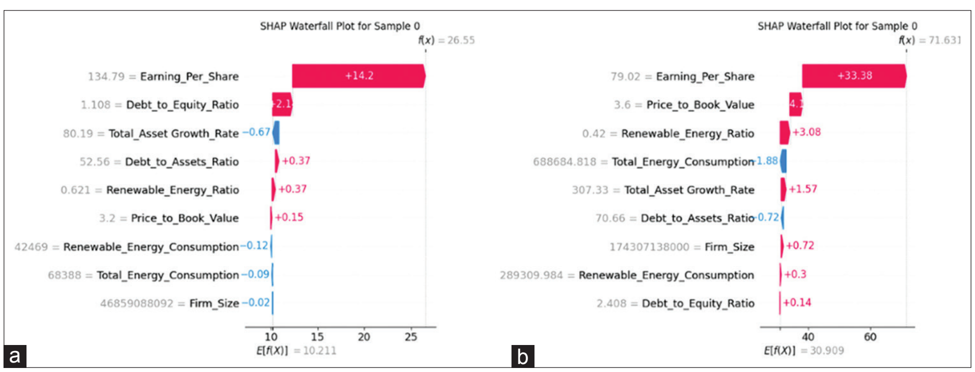



**Figure 4:** Distribution of Shap Values. (a) SHAP beeswarm plot illustrating the distribution of SHAP values for each feature in predicting ROA, (b) SHAP beeswarm plot illustrating the distribution of SHAP values for each feature in predicting ROE

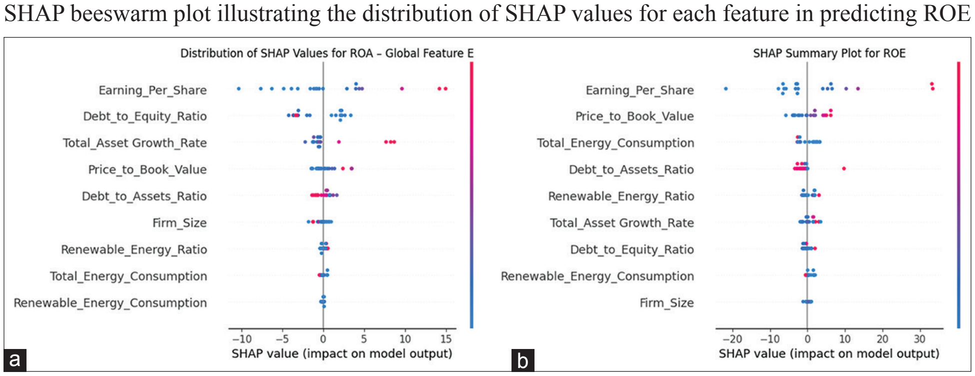


**Table 3: Performance comparison of regression models for ROA**

| Model | $R^2$ | RMSE | MAE | MAPE (%) |
|---|---|---|---|---|
| XGBoost | 0.8407 | 0.0142 | 0.0104 | 12.3457 |
| Random Forest | 0.7526 | 0.0197 | 0.0145 | 16.5824 |
| LightGBM | 0.6500 | 0.0243 | 0.0184 | 20.7631 |

**Table 4: Performance comparison of regression models for ROE**

| Model | Test $R^2$ | RMSE | MAE | MAPE (%) |
|---|---|---|---|---|
| RandomForest | 0.5987 | 15.1866 | 12.8364 | 65.0064 |
| XGBoost | 0.5807 | 15.5232 | 12.9728 | 75.4491 |
| LightGBM | 0.4885 | 17.1458 | 13.6288 | 158.5239 |

Forest, and LightGBM algorithms were applied to estimate the ROA and ROE target variables using the input variables determined in the previous section. The applied ML algorithms were subjected to hyperparameter optimization and 5-fold cross-validation. Accordingly, the best prediction models of the ML algorithms were created. The results are presented in Table 3 for ROA and Table 4 for ROE along with the performance metrics.

As seen in Table 3, hyperparameter optimization and 5-fold cross-validation were applied to ML algorithms for ROA. The best prediction models were created with the algorithms. As a result of applying the test data with the best prediction models obtained, the XGBoost algorithm was found to be the best prediction model with an $R^2$ value of 0.8407. Then, the best prediction model created with the Random Forest algorithm is the second-best performing algorithm with an $R^2$ value of 0.7526. XGBoost and Random Forest can explain a significant portion of the ROA variable. The ROA forecasting model created with LightGBM showed the lowest performance with an $R^2$ value of 0.6500 compared to the other two algorithms.

In Table 4, as a result of the evaluation of the best models used for ROE forecasting with the test data, it is determined that the model with the highest accuracy rate is Random Forest. This model made the best prediction with an $R^2$ value of 0.5987. The second-best performing model was XGBoost with an $R^2$ value of 0.5807. Both models are able to explain the ROE target variable at a moderate level. On the other hand, the LightGBM model underperformed compared to the other two algorithms with an $R^2$ value of 0.4885.

## 5. CONCLUSION AND POLICY IMPLICATIONS

The aim of this study is to analyze the relationship between the renewable energy consumption and the financial performance of the enterprises in the BIST Sustainability Index with the XAI method and to evaluate its predictability with machine learning methods. Within the scope of the research, annual data of the enterprises for the period 2021-2023 were used. Non-financial data of these enterprises were obtained from the Sustainability Reports, Annual Reports, and Integrated Reports, while financial accounting data were obtained through Finnet2000plus. The data generated within the scope of the study were analyzed with SHAP, one of the XAI methods, and the effects and importance levels of input variables on the target variables ROA and ROE were examined. Then, the input variables with the highest contribution were identified. In the study, forecasting models were developed with machine learning algorithms such as XGBoost, Random Forest, and LightGBM based on financial accounting indicators such as ROA and ROE to predict financial performance. To obtain the best performance, hyperparameter optimization and 5-fold cross-validation with the GridSearchCV method are applied. Finally, the performances of the prediction models were compared, and the most successful model was determined. Some of the variables in the study consist of non-financial indicators (RREC, TEC, RER), while others consist of both financial accounting indicators (ROA, ROE, D/E, D/A, TAG, TEG) and market-based performance indicators (e.g., PB, EPS, and FS).

According to the result of the model in which ROA is used as the target variable in the SHAP analysis, renewable energy consumption has a very limited negative effect on ROA, whereas an increase in the Renewable Energy Ratio makes a positive contribution to ROA, albeit at a low level. According to the results of the model in which ROE is used as the target variable, renewable energy consumption has a low positive effect on ROE. Earnings Per Share, with the highest average SHAP value, was found to be the most effective variable for explaining ROA and ROE prediction models compared to renewable energy data. Again, these variables increase the explanatory power of the model. These findings are in line with Morina et al. (2021) and Shin et al. (2018), but unlike the studies of Dopierała et al. (2022) and Martí-Ballester (2017), the use of renewable energy has a small effect on enterprises' financial performance.

When enterprises invest in renewable energy, various accounts in their financial statements are directly and indirectly affected. These effects change tangible fixed assets, liabilities, and equity. From an accounting perspective, the results suggest that renewable energy investments may put pressure on ROA in the short term. This may be due to the increase in the assets of the enterprise in the short term during the transition to renewable energy and the high initial and operational costs (for example, maintenance-repair costs and management expenses in the early periods). The data analyzed within the scope of the research show that enterprises' renewable energy consumption has significantly increased, especially in 2023. While in 2021, renewable energy consumption was at a relatively low level, it started to increase in 2022, and this trend became more pronounced in 2023. The process of returning renewable energy costs to revenue generation can have a long-term effect. Tax incentives and government support can positively affect long-term profitability. On a global scale, various policies and regulations are coming into force to encourage the transition to renewable energy in line with the zero-emissions target by 2050. In Turkey, advantageous tax practices and government subsidies are available. Companies can develop strategies to support sustainable growth by managing their financial situation in line with accounting records and financial accounting indicators through energy policies.

This study contributes to the literature on integrating the SHAP method, an XAI method, into financial accounting. Although machine learning methods generally offer high accuracy, the interpretability of decision processes can be limited. In this study, SHAP analysis, which is used differently from traditional methods, provides clarity and interpretability to the financial performance values predicted by the model and provides more transparent and applicable results to information users. In particular, the higher performance of the XGBoost algorithm in ROA estimation and the Random Forest algorithm in ROE estimation reveals that the choice of model may differ according to the financial performance indicator to be estimated; this situation emphasizes the strategic importance of choosing an algorithm suitable for the structural characteristics of financial variables.

This study has some limitations. The sample is limited to companies listed on the Borsa Istanbul Sustainability Index to access energy data. In future research, more comprehensive analyses of different sectors and global markets can be conducted. At the same time, the results can be compared to different XAI models and deep learning algorithms. In addition, the indirect effects on financial performance can be better understood by adding government incentives and policy variables. For emerging economies, such as Turkey, companies' transition to renewable energy can be costly. Therefore, incentives for transitioning to renewable energy are important, and it is important to ensure cost-effectiveness.

In conclusion, although the transition to renewable energy may have some negative impacts in the short term, it becomes a critical element that increases the profitability of companies in the long term with the right accounting policies and supports their sustainability goals. Therefore, companies and investors can shape their strategies in this area using data-driven and artificial intelligence-based approaches. In addition, this study will help businesses make more informed and strategic decisions regarding transitioning to renewable energy.

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