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Modeling the link between environmental, social, and governance disclosures and scores: the case of publicly traded companies in the Borsa Istanbul Sustainability Index

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Abstract

This study constructs a proposed model to investigate the link between environmental, social, and governance (ESG) disclosures and ESG scores for publicly traded companies in the Borsa Istanbul Sustainability (XUSRD) index. In this context, this study considers 66 companies, examining recently structured ESG disclosures for 2022 that were published for the first time as novel data and applying a multilayer perceptron (MLP) artificial neural network algorithm. The relevant results are fourfold. (1) The MLP algorithm has explanatory power (i.e., R²) of 79% in estimating companies' ESG scores. (2) Common, environment, social, and governance pillars have respective weights of 21.04%, 44.87%, 30.34%, and 3.74% in total ESG scores. (3) The absolute and relative significance of each ESG reporting principle for companies' ESG scores varies. (4) According to absolute and relative significance, the most effective ESG principle is the common principle, followed by social and environmental principles, whereas governance principles have less significance. Overall, the results demonstrate that applying a linear approach to complete deficient ESG disclosures is inefficient for increasing companies' ESG scores; instead, companies should focus on the ESG principles that have the highest relative significance. The findings of this study contribute to the literature by defining the most significant ESG principles for stimulating the ESG scores of companies in the XUSRD index.

Keywords: ESG disclosures, ESG scores, New ESG reporting scheme, Artificial neural network, Borsa Istanbul Sustainability Index, Türkiye

JEL Classification: C45, G34, G38, M48, O16

Introduction

In recent years, environmental issues have sparked growing concerns, leading to increased awareness that has impacted investment decisions (Batrancea 2021a; Depren et al. 2023; Kartal et al. 2023; Pata et al. 2023; Ulussever et al. 2023a). This atmosphere has compelled companies to align strategies with environmental, social, and governance (ESG) principles that emphasize the need to actively participate in environmental activities and disclose such efforts to mitigate environmental



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externalities (Azmi et al. 2019). As ESG investing, also known as socially responsible investing, has gained prominence, companies' disclosure of information regarding practices that impact investors, the environment, and the community has become a crucial investor demand (Ellili 2022). ESG investing is an investment strategy that evaluates a company's approach to ESG factors including action on climate change, environmental protection, and broader impact on society and human rights, while endeavoring to generate returns and develop portfolio allocation strategies (Wang et al. 2023). The COVID-19 pandemic further emphasized the links between environmental and economic sustainability, human health, and climate change, stressing the significance of ESG investing (Adams and Abhayawansa 2022). Companies recognize that solely providing financial information is insufficient for contemporary investors and have moved toward comprehensive reports on ESG, sustainability, and other intangible corporate practices that are demanded by all types of stakeholders (Biondi and Bracci 2018). ESG disclosures refer to companies sharing public information regarding ESG performance and practices (Sariyer and Taşkın 2022). Such disclosures provide transparent and comprehensive statements about how a company manages and addresses key ESG issues that may impact its stakeholders and the broader society.

The rising awareness of ESG activities has encouraged companies to focus on sustainability and triggered the development of ESG indices in various stock markets worldwide. Companies have started to associate themselves with sustainability indices to advertise ESG practices and attract individual and institutional investors (Albuquerque et al. 2019). ESG-integrated funds received over \$500 billion in investments in 2021, representing a 55% growth in ESG-oriented products, despite the economic downturn caused by the COVID-19 pandemic (Morningstar 2021). Increased sustainable investing despite the economic slowdown during the pandemic indicates the popularity of ESG portfolios. ESG portfolios are considered to be reliable instruments during times of turmoil, and performance during the pandemic further stimulated investor interest in companies' ESG disclosure, particularly during uncertain periods (Pastor and Vorsatz 2020; Çağlı et al. 2022). Previous studies have demonstrated that firms with higher ESG ratings and ESG activities face lower risk and exhibit greater resilience during periods of economic instability (Ferriani and Natoli 2020; Broadstock et al. 2021).

Amid the increasing significance of ESG disclosures for advancing ESG investing, this study examines the link between ESG disclosures and ESG performance in the context of 66 publicly traded companies (PTCs) listed in the Borsa Istanbul Sustainability (XUSRD) index that released ESG reports for the year 2022. The study investigates whether ESG disclosures can be used to predict companies' ESG scores, adopting multilayer perceptron (MLP) artificial neural network (ANN) approach to assess the explanatory power of ESG disclosures and identify the relative significance of different ESG principles in the common, environmental, social, and governance pillars, determining the specific ESG principles that companies should prioritize to improve ESG scores. The study's primary contribution is deepening the understanding of the ESG disclosure–score relationship in emerging markets, using a recent dataset and advanced computational methods, and determining the significance of different ESG principles.

This study addresses a critical gap in the existing literature on ESG practices and performance. While previous research has presented analyses and estimations of ESG performance in equity markets in developed or high-depth markets, this study offers a distinct and noteworthy contribution by examining the specific context of PTCs within the XUSRD index, expanding the knowledge base regarding ESG practices in emerging markets. Furthermore, the study uses a recently structured dataset, emphasizing the relevance of up-to-date information for investigating the connection between ESG disclosures and ESG scores. By employing an MLP algorithm, this research pioneers the use of advanced computational methods for ESG data analysis. Finally, this study confirms the correlation between ESG disclosures and scores, and the findings also identify the relative significance of specific ESG principles in different pillars, offering actionable insights for companies and stakeholders to prioritize ESG efforts effectively. In summary, this study makes a valuable and multifaceted contribution to the literature, advancing the understanding of the intricate relationship between ESG disclosures and ESG scores, particularly in emerging markets, and demonstrating the potential of cutting-edge methodologies in ESG research.

The study yields several noteworthy findings and managerial implications. First, the results confirm the significance of ESG disclosures and suggest focusing on deficient ESG principles, while maintaining a strong positions in common principles. Second, managers should not take a linear approach to improve ESG scores; instead, they should concentrate on reporting principles that have a higher effect on ESG scores. Third, as this approach might seem like pushing managers to engage in "greenwash," the results suggest working gradually on less significant ESG principles. Even the least important principles, such as "Disclosing international reporting standards embraced in reporting" (S15), should be considered for improvement, albeit with lower priority. Moreover, this study suggests policy implications for policymakers to make explanatory notes for each ESG reporting principle mandatory, which will increase transparency and accuracy in ESG reports. Moreover, policymakers should stimulate the use of external parties (i.e., auditors) to confirm the accuracy of ESG disclosures before they are published.

The remainder of this paper proceeds as follows. "Literature review" section presents a literature review; "Methods" section provides the study's methods; and "Results" section displays the results. Finally, "Conclusion and policy implications" section concludes the study.

Literature review

ESG scores and disclosures are a relatively new topic that has been discussed in the literature from different perspectives. ESG reporting is closely related to standards, regulations, legitimacy, and stakeholders (Deegan 2014). The first ESG rating agency, Eiris, was established in France in 1983, followed by three different agencies in the US in the 1990s (Berg et al. 2022). Disclosing ESG information has various economic implications, including capital constraints, lower capital cost, and better prediction of companies' future financial status (Amel-Zadeh and Serafeim 2018). Positive developments in ESG statements imply that companies engage in activities to improve society socially, institutionally, and environmentally through green transformation. In this context, researchers have examined the effectiveness of ESG scores and disclosures and their interactions

with certain social and economic indicators. Tsang et al. (2022) provided a detailed literature review on ESG disclosure and examined 132 articles on corporate social responsibility (CSR)/ESG ratings.

The significance of ESG disclosures for stakeholders can be explained by stakeholder theory and agency theory. Stakeholder theory postulates the responsibilities of companies to various stakeholders such as shareholders, customers, employees, and society at large (Freeman and Reed 1983; Freeman 1984). The growing interest in ESG disclosure from various parties like investors, traders, companies, and regulatory authorities is not surprising. Agency theory also sheds light on companies' and investors' ESG activities (Jensen 1986). Shareholders are increasingly concerned about ESG performance and disclosure, which serve as mechanisms that reduce information asymmetry between principals and agents.

ESG studies have generally been based on the recent past. Halbritter and Dorfleitner (2015) found that ESG portfolios between high and low ESG-rated companies did not differ over the period 1991-2012. Siew et al. (2016) demonstrated a negative interaction between ESG disclosures and market information asymmetry for 683 companies on the New York Stock Exchange from 2007 to 2011. Lokuwaduge and Heenetigala (2017) asserted that the reporting regimes of 30 companies in the mining and metals sector in Australia influenced ongoing motives for ESG reporting and stakeholder engagement promotes ESG disclosure. Fatemi et al. (2018) concluded that the strength of ESG disclosures supported increased firm value for 403 US companies from 2006 to 2011. McBrayer (2018) examined Bloomberg data for 1450 companies from January 1, 2006 to December 31, 2015, determining that variability in the quality of ESG disclosure decreases with rising management tenure and that top manager changes disrupt ESG disclosure. Arayssi et al. (2020) examined the impact of Board structure on ESG disclosures using multiple panel data regression from 2008 to 2017 for Gulf Cooperation Council countries, revealing that Board independence and greater female Board participation facilitate ESG activity reporting, whereas ESG reporting is less prioritized in boards chaired by chief executive officers.

Mohammad and Wasiuzzaman (2021) found a negative relationship between comparative advantages and ESG disclosures for 661 companies listed in Bursa Malaysia from 2012 to 2017. Murata and Hamori (2021) determined that ESG disclosures reduce the risk of European and Japanese stock price crashes, but do not have any impact on US markets. According to Raimo et al. (2021), ESG debt disclosures had a negative impact on the cost of financing for 919 companies listed in Standard and Poor's 1200 Global Index from 2010 to 2019, indicating that companies with high ESGs can access financing opportunities more easily. Yu and Van Luu (2021) determined that political rights and corruption have no significant impact on ESG disclosures for 1963 large-scale companies in 49 countries. The results of the study also reveal that increased foreign ownership does not have an impact on increasing ESG disclosures. Avramov et al. (2022) found that ESG uncertainty increases the market risk premium and decreases the demand for stocks in the US stock market from 2002 to 2019. Berg et al. (2022) demonstrated that 6% of the differences in ESG ratings are due to weight, 38% to scope, and 56% to measurement, examining data from 2014 and 2017 compiled from six different ESG rating agencies for 924 companies. Da Silva (2022) found that ESG disclosures for 44 countries reduced company-specific crash risks from 2007 to 2019.

Feng et al. (2022) revealed a negative relationship between ESG ratings and the risk of a stock price crash in China from 2009 to 2020. Aevoae et al. (2023) found that ESG helps reduce banking system risk using a dynamic panel model for 367 banks listed in 47 countries from 2007 to 2020. Using Korean data covering 2012–2018, Bae et al. (2021) determined that ESG ratings and stock price risk are negatively associated and CSR has a positive influence on minimizing stock price pressure. Bissoondoval-Bheenick et al. (2023) argued that better media coverage reduces asymmetry in ESG investments from 2007 to 2020 for 5648 companies in G20 countries. Deng et al. (2023) concluded that ESG ratings minimize financial constraints, reduce the risk of a stock price crash, and increase labor productivity for 2833 Chinese companies from 2015 to 2021. Fiordelisi et al. (2023) revealed a negative relationship between the ESG of 90 banks and future stock price crashes in 22 European countries from 2015 to 2021. Rahman et al. (2023) found that ESG has a positive impact on the performance of 225 companies from 2016 to 2020 using Tobin's Q. Singhania and Saini (2023) determined that integrated reporting and sustainability reporting should be developed to popularize the application of ESG by applying a cross-country comparative ESG approach for 13 developed and developing countries. Wang et al. (2023) concluded that ESG investments reduced China's greenhouse gas emissions from 1990 to 2021.

The above studies examined the interactions of ESG disclosures, ratings, and investments using various macroeconomic variables. Overall, researchers have emphasized that ESG promotes sustainable development and reduces the risk of stock crash risk. However, previous research has not yet analyzed the explanatory proportions of the common environmental, social, and governance pillars of ESG disclosures on ESG scores. Moreover, the relative and absolute significance of these ESG principles has not been examined. Another research gap is that no study has modeled ESG scores for the PTCs in Türkiye; thus, this study contributes to the current literature by demonstrating the correlation between ESG disclosures and ESG scores using MLP ANN modeling for Türkiye.

Methods

Data

This study presents a model regarding the link between companies' ESG disclosures (i.e., ESG reports) and ESG scores in the XUSRD index. The XUSRD index includes a total of 72 companies. However, six companies were excluded from the analysis because they had not published ESG reports for 2022 by the end of April 2023, which was the time period selected for this study. Hence, the study includes 2022 ESG reports from 66 companies in the XUSRD index, which are detailed in Additional file 1: Appendix S1, and 54 independent variables. All independent variables include simple binary "yes" or "no" options.

Data for companies' ESG disclosures are obtained from the Public Disclosure Platform (PDP 2023), and data for companies' ESG scores are obtained from Refinitiv (2023). Table 1 presents the main points for the study's variables.

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Variable explanation	Unit	Data source
ESG Scores of Companies*	Basis point	Refinitiv (2023)
ESG Disclosures of Companies	Multiple choice	PDP (2023)
*Shows the dependent variable		

Table 2 A statistical summary of ESG notes

	ESG score	E pillar	S pillar	G pillar
Mean	74.66	75.82	81.28	64.18
Median	75.57	76.54	83.26	64.19
Maximum	92.67	99.23	98.48	90.33
Minimum	48.57	44.64	54.35	36.62
Standard deviation	10.93	13.92	12.31	16.06
Coefficient of variation	14.64	18.36	15.15	25.02
Skewness	- 0.27	-0.19	- 0.47	0.00
Kurtosis	2.33	2.23	2.05	1.74
Jarque–Bera	2.03	2.04	4.91	4.37
Jarque–Bera probability	0.3629	0.3611	0.0857	0.1122
Observation (Companies)	66	66	66	66
Observation (Principles)	54	54	54	54
Observation (Total)	3564	3564	3564	3564

Table 2 presents the descriptive statistics of companies' ESG scores, which are detailed for each company in Additional file 1: Appendix S2.

Table 2 presents various statistical metrics for ESG scores and their main pillars (E, S, G). These measures provide insights into the central tendency, dispersion, skewness, kurtosis, and normality of the data. The ESG scores have a mean of 74.66, indicating that companies perform relatively well in terms of ESG factors on average. The median values, representing the middle score in the sorted list, indicate the central tendency of the data distribution. The median values are 75.57, 76.54, 83.26, and 64.19 for the ESG score, E-pillar, S-pillar, and G-pillar, respectively. This result suggests that more than half of the companies are above these values, while the remainder are below these scores. The coefficient of variation, which is calculated as the ratio of the standard deviation to the mean, is a relative measure of variability that provides insights into the degree of dispersion relative to the mean. For example, the E-pillar has a coefficient of variation of 18.36, indicating a higher degree of variability compared with other categories.

Skewness measures the asymmetry of the data distribution, while kurtosis indicates how peaked or flat the data distribution is compared with a normal distribution. Negative values of skewness indicate a longer or stronger tail on the left side of the distribution. Therefore, it can be asserted that all factors, except for the G-pillar, have a slightly left-skewed distribution. Positive kurtosis values signify a relatively peaked distribution, while negative values imply a flatter distribution. In this case, all parameters have positive kurtosis values, ranging from 1.74 to 2.33. The Jarque–Bera test is used to assess the normality of the data distribution based on skewness and kurtosis, and the values given

Number of principles	Number of principles in the new reporting scheme	Number of principles included in the analysis*
In C pillar	10	12
In E pillar	25	24
In S pillar	15	16
In G pillar	2	2
Total	52	54

Table 3 A summary of ESG principles

*Because some principles either include multiple issues or are addressed to another principle or empty in the new EGS reporting scheme, researchers have had to make re-arrangements



Fig. 1 Methodological approach

for each parameter demonstrate that the distributions do not deviate from normality at a 90% confidence interval.

According to the regulations announced by the Capital Market Board of Türkiye (CMB) on June 23, 2022, companies defined by the CMB are required to publish ESG disclosures in 2023, starting with 2022 reporting (CMB 2023). In addition, these companies should use the ESG reporting scheme provided for ESG disclosures, employing multiple choice (i.e., yes, no, partially, unrelated) and explanation columns. ESG principles fall under different sections, which are detailed in Additional file 1: Appendix S3 and summarized in Table 3.

Obtaining companies' ESG disclosures from the PDP (2023) and making necessary rearranging the ESG reports, the researchers manually construct a consolidated dataset to be used in ANN modeling.

Methodological flow

Figure 1 illustrates the methodological approach, which involves three steps, including (1) data gathering, (2) empirical analysis, and (3) results and discussion.

The first step of the research process entails data collection from two distinct sources, Refinitiv (2023) and PDP (2023). This initial phase is the foundation for analysis and empirical research.

In the second step, the researchers conduct an empirical analysis of the dataset. This analytical approach includes several key procedures, including the use of descriptive statistics to summarize and describe the dataset. The dataset is also partitioned into separate training and testing subsets to facilitate ANN model development and evaluation. The application of ANN modeling techniques is conducted to uncover underlying patterns and relationships within the data. Variable significance analysis is also performed to ascertain the relative weights of different variables. Unlike panel data analysis, the machine learning-based ANN approach is resistant to heteroskedasticity, endogeneity, and multicollinearity problems. Moreover, the ANN method can be performed without applying leading unit root or cointegration tests as in panel data analysis (e.g., Mardani et al. 2020; Deng et al. 2022; Zhang et al. 2023). The machine learning-based ANN approach does not require an initial Hausman test or F-tests of first-generation panel data analysis. Because the dataset used in the study has no time or trend dimensions, the ANN is an assumption-free model, and because of the aforementioned advantages, this approach has recently been used by several researchers for ESG analysis (e.g., Raza et al. 2022; Svanberg et al. 2022; Wu et al. 2023). In this study, employing a data splitting methodology, in which 80% of the dataset is used for training and 20% of the dataset is used for testing aims at achieving a high degree of model robustness; however, constraints regarding the size of observations in the training and test datasets is noteworthy. The small number of observations within these datasets also precludes the application of conventional analytical techniques.

The ESG score is treated as the dependent variable, while a set of principles are employed as independent variables.his study uses the following primary empirical model, following the step-by-step methodology outlined above:

$$ESG = f(C_1, \dots, C_{12}, E_1, \dots, E_{24}, S_1, \dots, S_{16}, G_1, G_2, w_{ij}) + \varepsilon$$
(1)

where C, E, S, and G represent common, environmental, social, and corporate governance principles, respectively. w_{ij} and ε are weights used in the hidden layers and the error term. The weighting approach of the ANN is expected to assign each ESG pillar a different weighted impact on ESG score.

The third step involves the presentation of the results and subsequent discussion. This section incorporates a comprehensive examination and interpretation of the findings. The researchers draw conclusions from the empirical analysis, encapsulating the main insights and outcomes of the study. In addition, policy implications are elucidated to underscore any considerations or limitations that policymakers should be aware of when implementing potential policies based on the findings. The discussion also includes an exploration of the study's limitations and suggests future research to overcome these limitations and advance current knowledge in the field.

Artificial neural network model

Modeled on the structure and functioning of the human brain, ANNs are a class of machine learning algorithms designed to recognize patterns and make predictions based on input data. The MLP is one of the fundamental types of neural networks commonly used in various applications including image recognition, natural language processing, and time series analysis.

The MLP is a feedforward ANN model consisting of several layers of interconnected nodes called artificial neurons or perceptrons. The model consists of an input layer, one or more hidden layers, and an output layer. In the MLP, each neuron in the network applies an activation function, which is employed across all neurons in a multilayer perceptron to produce a functional mapping of the weighted inputs to the respective neuron outputs. The activation function introduces nonlinearities into the model and allows it to learn complex relationships between inputs and outputs (Rumelhart et al. 1986).

Net input and output are obtained by Eq. (2) and (3), respectively;

$$NetInput = \sum_{i=1}^{n} x_i w_i \tag{2}$$

$$\varphi = f(NetInput) = \frac{1}{1 + e^{-NetInput}}$$
(3)

Due to the fully connected nature of MLPs, notably, every node within a given layer establishes connections, which are governed by weight coefficients (denoted as w_{ij}) with every node in the subsequent layer. Common activation functions used in MLP include the sigmoid function, the hyperbolic tangent function, and the rectified linear unit.

The most important aspect of the MLP algorithm is the perceptron learning process, in which modification of connection weights occurs subsequent to the processing of individual data elements. This modification is based on the quantified disparity between the output and the anticipated result (error), which facilitates the adaptation of the network. The next step is fine-tuning node weights by incorporating adjustments to minimize the error across the complete output corresponding to the *n*th data point, as expressed in Eq. (4).

$$\varepsilon_n = \frac{1}{2} \sum_{output \ node \ j} e_j^2(n) \tag{4}$$

where $e_j(n)$ represents the error in node *j* in the *n*th data point. $d_j(n)$ and $y_j(n)$ are the desired target value and value produced by the perceptron, respectively. The change in weights (w_{ji}) is calculated using gradient descent, which is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function as expressed in Eq. (5).

$$\Delta w_{ji}(n) = -\eta \frac{\vartheta \varepsilon(n)}{\vartheta v_j(n)} y_i(n)$$
(5)

where y_i and η are the output of the previous neuron *i* and the learning rate, respectively. Finally, Eq. (5) can be expressed using the derivative function as in Eqs. (6) and (7).

$$-\frac{\vartheta \,\varepsilon(n)}{\vartheta \,v_j(n)} = \varepsilon_j(n)\phi/(v_j(n)) \tag{6}$$

$$-\frac{\vartheta \varepsilon(n)}{\vartheta v_j(n)} = \phi'(v_j(n)) \sum_k -\frac{\vartheta \varepsilon(n)}{\vartheta v_k(n)} w_{kj}(n)$$
⁽⁷⁾

Adjustments are made to the output layer weights (w_{kj}) based on the derivative of the activation function (ϕ') to update the weights of the hidden layer. This process implements backpropagation for the activation function (Haykin 1998).

Figure 2 illustrates the logic of the ANN model.

The primary purpose of the MLP is to determine the underlying relationships between the input data and the desired outputs by adjusting the weights and biases of



Fig. 2 Logic of the ANN model

the neurons through a process called backpropagation. During training, the algorithm iteratively adjusts the weights to minimize the difference between the predicted outputs and the actual outputs using an optimization algorithm such as gradient descent. This is typically accomplished using a cost function that quantifies the error between the predicted outputs and the ground truth (LeCun et al. 2015). The cost function most commonly used in MLP is the mean squared error.

This study employs the backpropagation algorithm to optimize the MLP to calculate the gradients of the weights and biases concerning the cost function, which allows researchers to update parameters through gradient descent or other optimization algorithms. By iteratively adjusting the weights and biases using backpropagation, an MLP can learn to approximate complex functions and make predictions based on input data.

Results

Artificial neural network model

The next step in the ANN methodology is modeling the ESG scores using the MLP algorithm, which incorporates one dependent variable and a set of 54 independent factors (i.e., the ESG reporting principles). Using random selection, 80% of the observations are assigned to the training set, while the remaining 20% are assigned to the test set. The training set includes 53 companies and the test set includes 13 companies, which corresponds to the dataset of 66 companies. Consequently, the training dataset incorporates

almost as many independent variables as the number of observations. For this reason, as an assumption-free model, the MLP is preferred rather than classical models assuming no multicollinearity, heteroskedasticity, and normal distribution of variables. The MLP framework has a structure with two hidden layers, employing a hyperbolic tangent function as the activation function. The chosen error function is the sum of squared errors. The first hidden layer consists of 20 neurons, while the second hidden layer encompasses 10 neurons.

After iterative calculations within the MLP algorithm, the researchers run a performance evaluation of model for the training and test datasets. The root mean square error (RMSE), mean absolute error (MAE), and R^2 metrics determine the predictive accuracy and goodness-of-fit of the MLP algorithm in modeling the companies' ESG scores. The summary results for these performance criteria are presented in Table 4.

For the training dataset, a RMSE value indicates that the average magnitude of the residuals between predicted and actual ESG scores is approximately 5.327 units. The MAE value reflects an average absolute difference of approximately 4.430 units between predicted and actual ESG scores. Finally, the R^2 value indicates that the MLP algorithm captures 78.6% of the variability in ESG scores within the training dataset.

For the test dataset, the RMSE value signifies an average absolute deviation of approximately 4.935 units between predicted and actual ESG scores. The MAE value of 3.757 denotes an average absolute difference of roughly 3.757 units between predicted and actual ESG scores. The R^2 value shows that the MLP algorithm explains 79.1% of the variability in ESG scores within the test dataset.

Overall, the prediction accuracy and goodness-of-fit criteria indicate that the MLP algorithm demonstrates satisfactory performance in predicting ESG scores. The relatively low RMSE and MAE values, along with moderate to high R^2 values for both datasets, suggest that the algorithm provides a reasonable fit to the data.

Figure 3 illustrates the relationship between the actual and predicted values from the MLP model for the training and test datasets, where the x-axis represents the actual values and the y-axis represents the predicted values. A desirable model would yield data points that cluster closely around the black diagonal line.

Figure 3 shows that the actual and predicted values of the training and test datasets are in proximity to one another, suggesting that the MLP model achieves a satisfactory level of accuracy, as evidenced by the alignment of data points with the diagonal line.

Variable significance analysis

The concept of relative variable significance in an MLP model refers to assessing the influence or contribution of the input variables to the predictions of the model. It can be used to determine which variable has a stronger influence on the performance of the model. The technique used for variable significance in an MLP model is known as weight

ANN model	Training	Training				
	RMSE	MAE	R ²	RMSE	MAE	R ²
MLP algorithm	5.327	4.430	78.6%	4.935	3.757	79.1%

etrics



E16 41.3% C10 43.5% E24 42.6% S6 15.9% S4 55.6% C5 100.0% E21 S13 G2 E14 29.4% S2 25.3% 5 2% 51.3% C7 24.6% E2 19.3% S12 E12 19.0% 50.3% S5 24.1% 18.9% E17 C6 E8 **S**14 23 09

Fig. 4 The relative importance of the ESG principles

importance analysis. It evaluates the significance of variables based on the magnitude of the weights assigned to each variable in the model. Figure 4 shows the relative significance of variables for each ESG principle used in MLP modeling.

Figure 4 presents the variable codes and their corresponding significance (importance/ weight), expressed in percentages. The results reveal that the C5 variable is the most significant factor influencing ESG scores. After C5, variables S7, E11, E3, and S4 also demonstrate considerable significance in determining ESG scores. Table 5 displays the principles included in the analysis and their corresponding variable significance.

Table 5 demonstrates that the C pillar incorporates a total of 12 principles that account for 21.04% of the overall variable significance. This finding suggests that the common principles exert a moderate influence on the comprehensive analysis conducted. In contrast, the E-pillar encompasses 24 principles that account for a substantial 44.87% of the total variable significance. This high proportion indicates that the environmental principles within all pillars have an overwhelming significance on the results of the analysis. The S-pillar encompasses 16 principles, accounting for 30.35% of the total variable significance, implying that the social principles also have remarkable significance within

Pillar	Number of principles included in the analysis	Total absolute variable importance (%)
C pillar	12	21.04
E pillar	24	44.87
S pillar	16	30.35
G pillar	2	3.74
Total	54	100.00

fable 5 Summary o	f variable importance	of each ESG pillar
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 Table 6
 Details of the most effective five ESG principles

Pillar	Code	Principle detail	Absolute importance (%)	Relative importance (%)
Common	C5	"The responsible committee and/or unit reports the activities carried out as per the policies during the year at least once a year to the Board of Directors"	5.83	100.00
Social	S7	"Discloses the activities for ensuring employee satisfaction during the reporting period"	4.33	74.24
Environment	E11	"Discloses its strategy and actions to combat the climate crisis"	3.47	59.51
Environment	E3	"Discloses the environmental targets included in rewarding cri- teria within the scope of performance incentive systems on the basis of stakeholders (board members, executives, employees, and so on)"	3.33	57.09
Social	S4	"Reports on progress in relation to actions for preventing and remedying discrimination, inequality, human rights violations, forced labor, and child labor"	3.24	55.65

the analysis. Conversely, the G-pillar comprises merely two principles, constituting a mere 3.74% of the total variable significance. This outcome suggests that governance principles have a relatively low impact on the analysis compared with the other pillars.

Table 6 presents a breakdown of the pillars, the corresponding codes, and detailed descriptions of the principles and their absolute and relative significance. The goal of the analysis is to determine the relative weight of each principle within the context of each pillar.

Principle C5 stands out within the common pillar with an absolute significance of 5.83%, representing the highest contribution in the analysis. This principle pertains to activity reporting by relevant committees and/or units in accordance with the Board policy. With a relative significance of 100%, this is the most influential principle of the common pillar.

Regarding the social pillar, principle S7 has an absolute significance of 4.33%, indicating considerable impact. This principle focuses on the disclosure of activities aimed at ensuring employee satisfaction during the reporting period. With a relative significance of 74.24%, this principle has a considerable role within the social pillar.

In the environmental pillar, principle E11, which emphasizes the disclosure of policies and measures to combat the climate crisis, exhibits an absolute significance of 3.47%. With a relative significance of 59.51%, this principle is a notable contributor to the environmental pillar. Similarly, principle E3 has an absolute significance of 3.33% under the environmental pillar. This principle highlights the disclosure of environmental targets incorporated into performance incentive systems and linked to stakeholders such as Board members, executives, and employees. With a relative significance of 57.09%, this principle occupies an important position in shaping the outcomes of the analysis.

Finally, within the social pillar, principle S4 has an absolute significance of 3.24%. This principle is about reporting progress on measures to prevent and eliminate various forms of discrimination, inequality, human rights violations, forced labor, and child labor. Its relative significance is 55.65%, which is a remarkable contribution to the social pillar.

Conclusion and policy implications

Conclusion

Since its inception, companies' ESG disclosure has become increasingly important (Sarıyer and Taşkın 2022). A growing number of stakeholders such as investors, corporate and green funds, and traders have expressed heightened interest in companies' ESG disclosures and scores. Companies are also interested in ESG disclosures and scores because of their significance to stakeholders and investors. This study constructs an ANN model to examine the link between ESG disclosures and scores. The study considers Türkiye's recently restructured ESG reporting scheme that pertains to PTCs. The study considers 66 companies in the XUSRD index that published complete ESG reports for the year 2022 in accordance with CMB regulations. To the best of knowledge, this link has not been extensively studied for PTCs in Türkiye using the recently restructured ESG reporting scheme and applying a novel ANN modeling approach.

The MLP algorithm has almost 80% R² value in estimating ESG scores by using ESG disclosures, which is above the acceptable threshold of 70%. Each pillar (C, E, S, G) has a different weight (i.e., absolute and relative significance) in total ESG scores, which varies for each ESG reporting principle. Based on absolute and relative significance, C5 is the most significant ESG principle among all principles, and is followed by S7, E11, and E3. Finally, the G-pillar has the lowest significance among all pillars. This study identifies the most important ESG reporting principles related to companies' ESG scores using ANN modeling that reveals the essential ESG priorities for Turkish companies based on actual published ESG disclosures (ESG reports) that include real deficits.

The study finds that ESG disclosures are correlated with ESG scores, which aligns with previous literature (e.g., Aydoğmuş et al. 2022). This study deepens the current knowledge by presenting information about which ESG principle should be prioritized by Turkish companies to raise ESG scores and potentially benefit from increased investor attention.

Policy implications

The novel ANN results primarily reveal a nonlinear relationship between ESG disclosures and ESG scores. Based on the results, various policy implications emerge. First, companies should determine the current level of ESG disclosure. By doing so, companies can focus on deficient ESG principles to maintain a positive position on the identified ESG principles. Companies can create a roadmap for their ESG disclosures from the perspectives of ESG scores. Second, companies should not take a linear approach to improve ESG scores. Instead of engaging in a misguided approach, companies are strongly advised to focus on closing any gaps in the significant ESG reporting principles that matter most for raising ESG scores, rather than treating all principles equally. This study provides important insights into the significant ESG reporting principles for increasing ESG scores. Therefore, it is possible for PTCs in the XUSRD index and other companies that use these scores as a benchmark to raise ESG scores much more quickly by prioritizing the development of specific principles.

Third, companies should consider the significance of each ESG principle and the cumulative significance of each pillar. As demonstrated by the ANN results, C5 (*The responsible committee and/or unit reports the activities carried out as per the policies during the year at least once a year to the Board of Directors*) is the most significant single ESG principle, followed by S7, E11, E3, and S4. In addition, the E-pillar has the highest cumulative significance (44.87%) followed by S (21.04%), C (30.35), and G (3.74). Thus, the main priority of PTCs in the XUSRD index should be to consider these weights to improve ESG scores.

Fourth, after making progress on the most significant principles, companies should naturally turn their attention to less significant ESG principles; for example, S15 (*Discloses the international reporting standards embraced in its reporting*), with an absolute significance 0.96% and E10 (*Sets short and long-term goals to reduce its environmental impact and discloses these goals and the progress, if any, as compared to the targets set in previous years*), with an absolute significance 0.66% as the least important two principles. Note that the most significant ESG principle (C5), which has 5.83% absolute significance, is 8.8 times more significant than the E10 principle in terms of ESG scores.

Overall, companies can benefit from ESG disclosures (Türkiye's new ESG reporting principles) in terms of ESG scores if they take a nonlinear approach and implement effective initiatives. Moreover, improving corporate ESG disclosures and scores can benefit companies' financial markets, societies, and nations by attracting increased foreign portfolio flows, supporting green finance and growth, and improving good governance that enables and advances environmentally friendly economic structure decisions. Therefore, evolving ESG disclosures and scores can contribute to overall national and global well-being.

Modeling the relationship between ESG disclosures and ESG scores is important for PTCs and other stakeholders (i.e., corporate investors, traders, funders, and governments), all of which are now able to obtain much more detailed information about companies' ESG practices to for informed decision making. Stakeholders can draw inferences from ESG disclosures about companies' ESG practices, and by extension, ESG scores. With this valuable information, investors can favor transactions with environmentally friendly companies and policymakers can impose sanctions on companies with lower environmental interests. Thus, the researchers assert that ESG disclosures and ESG scores can also be referenced to inform other parties.

In conclusion, this study clarified some issues for companies, regulators (i.e., the Turkish CMB in this study), and infrastructure organizations (i.e., the Central Securities Depository of Türkiye). The lack of a format that allows researchers to collect consolidated data for ESG disclosures is indeed a negative aspect, as the need for manual data collection may discourage researchers from conducting investigations. Therefore, it is crucial to establish and enforce the uniform collection of consolidated ESG disclosure data from PTCs based on common research preferences to promote scientific research in Türkiye regarding ESG disclosures and scores. In addition, the researchers argue that the inclusion of explanatory notes on each ESG reporting principle should be mandatory. In addition, the researchers posit that internal/external parties should confirm ESG disclosures prior to publication. The researchers identified some errors in companies' ESG disclosures for this reason.

Future perspective

Focusing on the case of Türkiye, which recently restructured its ESG reporting scheme, this study presents ANN modeling of the link between ESG disclosures and ESG scores for PTCs in the XUSRD index. The study considers 66 companies that published ESG reports for the year 2022 and apply the MLP algorithm to assign associated weights to 54 ESG principles. Using an extremely novel dataset and executing a comprehensive approach, this study demonstrates significant findings regarding the link between ESG disclosures and ESG scores.

Although the study provides several innovations, some limitations remain that can be considered as perspectives for future research. First, this study focuses on Türkiye because of the availability of recently restructured ESG reports that can be used to model ESG scores. This could encourage other countries to replicate Türkiye's practice in restructuring ESG reports, allowing new research to include such countries. Because this study focuses on PTCs in Türkiye, companies' internal conditions and external regulations and reporting approaches for the ESG disclosures and scores must logically be considered for each company outside of Türkiye. In addition, the study uses ESG scores from Refinitiv (2023). Although this is the best-known source of ESG scores, of course other ESG scores are available; thus, new studies can reference alternative ESG scores. New studies could even incorporate ESG scores from multiple sources to compare them in modeling. Furthermore, since only 2022 data are available, this research can be replicated in future years to include more longitudinal data. In addition, considering data availability, this study only includes 66 companies in the XUSRD index and future studies can incorporate ESG data for many more PTCs.

Although this study focuses on PTCs in the XUSRD index, future studies can consider examining other indices, such as the main index, corporate governance index, and other relevant constructs. Such new research could even compare indices. Furthermore, since this study applies the ANN approach, future research could evaluate the performance of other machine learning algorithms (Depren et al. 2021; Kılıç Depren et al. 2022; Ulussever et al. 2023b; Yae and Luo 2023) in addition to fuzzy approaches.

Moreover, new studies can construct new analytical frameworks to investigate the effect of ESG disclosures on stock market performance and financial assets, including equities and derivatives (Batrancea 2021b; Balcı et al. 2022a; Kartal et al. 2022a); stock market co-movements (Balcı et al. 2022b); sudden shocks and black swan cases such as the pandemic (Wen et al. 2019; Batrancea 2020, 2021c; Kartal et al. 2020, 2021, 2022b; Balcı et al. 2022c; Kanamura 2023; Kou 2023); economic indicators such as economic growth (Batrancea 2022; Batrancea et al. 2022a), financing opportunities for economic

actors, financial instructions (Batrancea et al. 2022b), green finance (Batrancea et al. 2021), and financial literacy (Long et al. 2023).

Finally, because some errors are detected in companies' ESG disclosures, improved data integrity that is assured by internal/external parties can provide much better results, and implementation of formal auditing procedures would be highly beneficial.

Abbreviations

Acronyms

ANN	Artificial neural network
CMB	Capital Market Board of Türkiye
COVID-19	Coronavirus 2019
CSR	Corporate Social Responsibility
ESG	Environmental, Social, and Governance
MAE	Mean absolute error
MLP	Multilayer perceptron
PDP	Public disclosure platform
PTC	Publicly traded companies
RMSE	Root mean square error
XUSRD Index	Borsa Istanbul Sustainability Index
UN	United Nations
USA	United States of America

Pillars in new ESG reporting scheme

C Pillar 0	Lommon Principles
E Pillar I	Environmental Principles
S Pillar S	Social Principles
G Pillar (Governance Principles

Supplementary Information

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Additional file 1. Supplementary Appendix.

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Author contributions

MTK: Conceptualization, Investigation, Methodology, Data Collection, Writing—original draft, Writing—review and editing; SKD: Formal analysis, Methodology, Software; UKP: Writing—original draft, Writing—review and editing; DT: Writing—original draft; TŞ: Writing—review and editing.

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Availability of data and materials

Data will be made available on request.

Declarations

Competing interests

The authors declare no competing interests.

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