International Journal of Applied Resilience and Sustainability, Volume 2, Issue 1, January 2026, pp. 78-96

Published online at Deep Science

International Journal of Applied Resilience and Sustainability

Journal homepage: https://deepscipub.com/ijars

# Explainable artificial intelligence for sustainable business performance: Integrating ESG metrics into AI adoption models

Anita Padhy [1], Nitin Liladhar Rane [2], Jayesh Rane [3]

[1] *First American Title, United States*
[2] *Architecture, Vivekanand Education Society's College of Architecture (VESCOA), Mumbai 400074, India*
[3] *K. J. Somaiya College of Engineering, Vidyavihar, Mumbai, India*

**Article Info:**
Received 25 November 2025
Revised 21 December 2026
Accepted 05 January 2026
Published 26 January 2026

**Corresponding Author:**
Jayesh Rane
E-mail: jayeshrane90@gmail.com



## Abstract

The rapid nature of the incorporation of artificial intelligence systems into the functioning of organizations has exposed a paradox that is critical in that when the algorithms of machine learning remain veiled the stakeholders cannot trust them and consequently hinder the sustainable transformation of business operations. Although there have been significant improvements in the capabilities of AI, their black-box character poses significant obstacles to their implementation in sustainability-oriented businesses, especially in the systems of environmental, social, and governance measurements and optimization. This is filled in the present research, where an integrated framework is developed and empirically supported to combine the explainable artificial intelligence principles with extensive ESG metrics to improve the performance of organizations in terms of sustainability. We used a mixed-methods design by gathering longitudinal evidence of multinationals in various sectors of the industry, spanning a specific period, using a structural equation model, hierarchical regression model, and machine learning classification algorithm as a form of analyzing the mediating mechanisms through which XAI transparency has effect on ESG performance outcomes. We realize that organizational sustainability performance scores on organizations practicing XAI-enabled systems of ESG monitoring are significantly much higher, with transparency systems that mediate the connection between AI adoption and ESG performances. Particularly, XAI implementation has been associated with a 23.7 percent increase in composite ESG scores with the environment performance responding the most. The study is theoretically useful in terms of expanding the scope of stakeholder theory and resource-based view theories to include algorithmic transparency as a strategic business resource and offers practitioners with practical models of how explainable AI technologies can be incorporated into sustainability management systems in order to generate quantifiable change in corporate environmental and social results.

Keywords: Explainable artificial intelligence, ESG, Sustainable business, Transparency, Corporate sustainability, AI governance

## 1. Introduction

The modern business environment is experiencing a historic merger of two transformative forces that are radically folding up the organization strategies and expectations of the stakeholders [1]. First, artificial intelligence technologies have ceased to be mere test tools of computation to become serious infrastructure mission down to the fabric of organizational activities, whether it is streamlining the supply chain or the customer relationship, or when it comes to the strategic decisions process [1,2]. The contemporary economy is experiencing exponential growth patterns which explains the centrality of the technology in developing competitive advantages in contemporary economies [3-5]. Second, environmental, social and governance-related issues have stopped being demonstration projects on the fringes of corporate social responsibility mission, and instead have turned into company-wide strategic demands that have significant influence upon firm valuation and investment decisions as well as

https://doi.org/10.70593/deepsci.0201005

regulatory compliance requirements [6,7]. Literature has shown that firms that have the best ESG performances record better financial returns, less cost of capital and stronger resilience in the basis of market volatility and thus organizations need to incorporate the best principles of sustainability across their operational models [2,8-10].

Nevertheless, the combination of these two dominating trends brings out a natural conflict that hinders their synergy abilities [1,11-12]. Although AI systems promise unique opportunities to solve complex types of sustainability data, optimize resource distribution, and forecast environments, they are characterized by high levels of obscurity that pose enormous obstacles to trust and regulation by the stakeholders [13-15]. The black-box behavior of advanced machine learning models, especially deep neural networks produce results by complex computational algorithms that can hardly be interpreted even by people with technical expertise [16]. Sustainability is due to this algorithmic opaque issue which makes it especially problematic in the context of sustainability where transparency, accountability and stakeholder engagement form the key values [16,17]. When companies implement opaque AI systems to mitigate environmental effects, evaluate social performance, or inform governance-based decisions, companies put the trust and legitimacy that sustainability efforts are meant to achieve at risk [12,18-20]. The introduction of explainable artificial intelligence is a viable source of solution to this tension as it will allow the creation of AI systems that will have their decision-making mechanisms that are understandable, verifiable, and trusted by various stakeholders [21-23]. XAI represents a variety of methods and approaches aimed at making algorithmic reasoning transparent, starting with post-hoc explanation models that explain black-box models, all the way up to models that are naturally interpretable that remain transparent during their execution [24,25]. Most recent work in XAI has focused on attention mechanisms emphasizing key input factors, counterfactual explanations that find out the smallest changes to make a prediction change, and extraction of rules that can be interpreted as decision rules in human form [26-28]. These developments pose opportunities to organizations to use AI opportunities to achieve sustainability management without compromising the transparency and accountability expected by the stakeholders.

Although the importance of XAI to sustainable business contexts is increasingly gaining momentum, available studies show that current studies have a number of fundamental weaknesses that limit the theoretical conceptualization as well as practical implementation [29-31]. First, the existing literature is somewhat diffuse in terms of the disciplinary scope, with the scholarship on computer science devoted to the technical XAI approaches, and the body of management research being focused on the issue of sustainability of organizations with little to no reference to the aspect of algorithmic thinking. This disintegration hampers the creation of structuralized formations that cut across technical capabilities with organizational sustainability demands [3,32,33]. Second, empirical research examining the XAI use in the business have overwhelmingly used only limited and technology-focused lenses that fail to consider the institutional pressures, complicated stakeholder involvement and organizational contingences that influence technology adoption and effect [4,34-36]. Third, the literature gives minimal recommendations on the manner in which organizations ought to structure XAI systems to support certain ESG measurement issues, sustainability performance outcomes, and trade-offs depending on the complexity and interpretability of the model.

A systematic review of peer-reviewed articles published during the period 2019-2024 in high-end journals indicates the following four major gaps in the current knowledge. To begin with, the literature does not include detailed empirical data on the impact of XAI implementation on the organizational ESG performance in a variety of industry setting and organizational structure. Although the theoretical arguments imply that the presence of algorithmic transparency should increase the sustainability outcomes due to the quality of decisions, the opportunity to engage stakeholders, as well as the opportunity to adhere to the regulations, these propositions are not proven in the context of rigorous quantitative methodologies. The current literature generally looks at either the technical performance of XAI or the ESG performance alone and not the relationships between them using longitudinal designs that can develop causal processes. Second, the existing literature does not offer enough theoretical bases to comprehend how and why XAI capabilities are converted into a better sustainability performance. Current explanations are more of descriptive than of theoretical, stating what benefits could be obtained without explaining the mechanisms behind them or what the boundaries of the explanations are. This conceptual gap constrains the level of scholarly knowledge on the relationship between XAI and ESG, as well as what helps organizations attain the superior application of such technologies. Third, the literature provides insufficient information on the mediating processes that XAI transparency has on the outcome of ESG. Although researchers admit that transparency probably influences sustainability performance via various avenues, such as increased stakeholder trust, higher quality of decisions, and greater accountability, they have not been well defined and have not been investigated empirically.

Fourth, current studies are mostly concentrated on the housed Western economies, and little concentration on the influences of institutional settings, regulation models, and cultural orientations are involved in determining the trends in the adoption and sustainability effects of XAI in different geographical locations. Such a geographical locality restricts the extrapolation of the already determined results and omits the aspects of the context, which could influence the XAI-ESG relationship and have a significant value. Also, the literature has a low temporal dynamics concern as most of the studies have cross-sectional design that is incapable of tracking how the XAI implementation effects are manifested over time or how the organizations can get more effective in leveraging these technologies through experience.

These are some of the key gaps into which this research will fill in using the following specific objectives. We first, build and empirically prove the full theoretical framework about how XAI capabilities are combined with the ESG performance dimensions, which is based on the perspectives of the stakeholder theory, the resource-based view visions, as well as on the institutional theory to develop how the notion of algorithmic transparency gives a sustainable competitive advantage. This framework outlines how implementation of XAI has an effect on the agenda of environment, social and governance results as well as the identification of critical contingencies that mediate such relationships. Second, to measure the impact of XAI adoption on ESG performance in various sectors of the industry, organizational sizes, and geographical locations objectively, we perform large-scale empirical research by using longitudinal data that consists of multinational companies. Third, we also apply higher statistical procedures such as the structural equation modeling and hierarchical regression analysis procedures to determine and quantify the mediating factors that XAI transparency impacts sustainability outcomes. The underlying tests of these analyses have specific hypotheses over the impact of transparency on stakeholder trust, quality of decisions and organizational learning besides tests of moderating effects of industry characteristics, intensity of regulation, and organizational capabilities. Fourth, we create and prove viable frameworks and application principles which allow organizations to successfully encompass XAI technologies in their sustainability management frameworks and overcome certain ESG measurements issues and optimization chances.

This study has various implications both to the academia and practice of management. Theoretically, we take the stakeholder theory based on showing how the concept of algorithmic transparency is an essential approach in developing and sustaining stakeholder belief in technology-based organizational actions. Although the application of the traditional version of the stakeholder theory highlights the significance of interpersonal communication and relationship management, our results indicate that transparency in automated decision systems is the factor that contributes to stakeholder perception and behavior in digitally transformed organizations in an ever-growing way. We also extend the resource-based view thinking by theorizing the XAI capabilities as a unique organizational asset that creates sustainable competitive advantages as reflected in the higher quality of decisions, stronger relationship with stakeholders and higher quality regulatory compliance.

The research methodologically contributes to the empirical research of the AI-sustainability intersections because it represents how longitudinal quantitative designs can effectively test the impact of technology implementation in a rigorous manner and can address the issue of temporal dynamics, selection effects, and reverse causality concerns that afflict the cross-sectional investigations. The conceptual framework that we have utilized presents a blueprint that could be used to undertake future studies that determine the effects of technology adoption in organizations that are intricate. In practice, we offer evidence-based models of XAI technologies usage in organizations to facilitate sustainability performance, and we can give certain recommendations concerning the choice of technology, implementation plans, interactions with stakeholders, and performance measurement tools. These contributions consider very practical needs where organizations are faced with mounting demands to improve technological innovations as well as improve performance in terms of sustainability.

## 2. Methodology

Overall, the study is based on a mixed-method research methodology, consisting of quantitative longitudinal research and qualitative case study that investigates the impact of explainable artificial intelligence application on organizational ESG performance. In our methodological design, we overcome the weaknesses of the technology adoption research where the spatial focus fails to provide a consistent perspective across time, responds to the selection effects, and seeks the mediating processes through which XAI capabilities are converted to the sustainability outcome. The study plan was deeply developed in pilot-tests of organizations in the period between January and June 2020 and led to changes in measurement tools, data collection methods, and analysis methods.

### *2.1 Sample and Data Collection*

We produced a comprehensive longitudinal data set of multinational companies that are active in the different industry sectors namely financial services, manufacturing, energy and utilities, technology, healthcare, retail, telecommunication, transportation, chemicals, food and beverage, mining and professional services. The sample selection was done by a stratified random sampling process that was aimed at ensuring that enough representatives were chosen to cover various sectors in the industry, various geographical areas, and various organizational sizes. The first version of sampling frames was based on the utilization of various sources of data. The overall response rates were 73.2 percent over a period of of data collection, which is a very high level of response compared to the average AI and sustainability survey response rates and represents how strategic the organizational performing companies consider the issue of AI and sustainability. The comparison of non-responding and responding organizations study through non-response analysis of the observable attributes of industry sector, firm size, geographical location, and previous ESG performance showed that there is no significant difference in the non-response analysis, which proved that our final sample is quite representativeness. To enhance quantitative surveys and archives with detailed qualitative data on the organization, we completed case studies through interviews in organizations that were chosen to ensure the broadest range of variation among several key dimensions such as the level of XAI implementation maturity, the industry setting, and ESG performance trajectories.

Dependent variables operationalized organizational ESG performance based on a multidimensional measurement system that exemplifies the different environmental, social, and governance aspects as well as allowing the calculation of the composite environmental, social and governance performance scores [37-40]. EPA of environmental performance embraced ten indicators which covered intensity of greenhouse gas emissions, the efficiency of energy consumption, optimization of water usage, rate of waste generation and recycling, mitigation of impact of biodiversity, application of the circular economy, adoption of renewable energy, violation of environmental compliance, green investments in environmental innovation, and supply chain environmental performance [4,41,42]. Individual indicators were each put on a 0-100 scale based on industry specific benchmarks and cumulative through a weighted average based on weighted sustainability reporting framework materiality scores.

The measurement of social performance covered eight dimensions namely worker health and safety performance, diversity and inclusiveness measures, labour rights performance, its investments in community engagement, human and labour rights due diligence performance, supply chain labour standards, employee development performance, and stakeholder satisfaction performance. Some of the nine items that were included in the evaluation of governance performance were board independence/diversity, alignment of executive compensation, strength of ethics and compliance program, quality of stakeholder engagement, transparency and disclosure processes, anti-corruption, data privacy and security, risk management system effectiveness, and protection of shareholder rights [43-45]. To achieve both empirically weighted aggregation schemes that would capture maximum variance with no arbitrary weighting schemes, composite ESG scores were calculated based on principal component analysis, these dimensional scores were put together.

The large single independent variable, XAI implementation intensity, was operationalized by using a multi-item construct that included a meaning of the width and depth of explainable AI adoption in the operations of organizations [9,46-48]. Breadth dimensions were used to capture the level of implementation of XAI technologies in various functions of the organization such as sustainability monitoring, supply chain management, risk assessment, customer engagement, human resource management, financial planning, and compliance monitoring. The dimension of depth measured levels of sophistication and maturity of XAI implementations in each functional area that considered issues such as the ability to generate explanations, availability of these explanations to stakeholders, intertwining with decision-making systems, and checking of accuracy of explanations. The results were measured by the seven-point Likert scales using the seven-point Likert scales to assess each dimension with a rating of implementation of XAI in an organization, and the ratings were confirmed by reviewing technical documentation and interviewing the leadership of the information technology.

### *2.2 Analytical Framework and Statistic Models.*

The form of our analytical work was to apply several statistical methods used complementary to each other, which aids in testing the interconnection between XAI implementation and ESG performance and overcoming the possible confounding factors and determining the mediating mechanisms. The main model of analysis was structural equation modeling that was employed to concurrently determine numerous relations among each other in an integrated path model to identify both direct and indirect effects of XAI on ESG performance and operating through mediating variables such as stakeholder trust, decision quality, and organizational learning abilities. The general structural model can be mathematically described as below:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{1}$$

where η represents the vector of endogenous latent variables including ESG performance dimensions and mediating constructs, ξ denotes the vector of exogenous latent variables including XAI implementation intensity and control variables, B captures structural coefficients for relationships among endogenous variables, Γ represents structural coefficients for effects of exogenous on endogenous variables, and ζ denotes the vector of equation disturbances. The measurement model linking latent constructs to observed indicators follows the specification:

$$y = \Lambda y\eta + \varepsilon \tag{2}$$

$$x = \Lambda x\xi + \delta \tag{3}$$

where y and x represent vectors of observed indicators for endogenous and exogenous latent variables respectively, Λy and Λx denote factor loading matrices, and ε and δ represent measurement error vectors. Model estimation employed maximum likelihood estimation with robust standard errors to account for potential non-normality in variable distributions.

The hierarchical regression model was used in supplement of structural equation modeling because the authors used it to examine the effects of the XAI implantations under varying organizational and environmental conditions. The regression model which was used as the baseline approximated the correlation between the implementation of XAI and composite ESG performance using controls of firm factors, industry impact, and time factors:

$$ESGit = \beta 0 + \beta 1XAIit + \beta 2Xit + \alpha i + \gamma t + \varepsilon it \tag{4}$$

where ESGit defines the aggregate score of a firm i on the ESG criteria at the current period t, XAIit defines the level of XAI implementation, Xit is a measure of a firm's control variables being the firm size, profitability, leverage, research and development intensity, past ESG performance, and industry competitiveness, ai is a fixed term of the firm that does not vary over time, gt is fixed terms in time that may cause joint shock, and eit is idiosyncratic error. The later specification of the model included interaction terms to observe the moderating hypothesis of the role of industry characteristics, regulatory intensity, and organizational capabilities on the XAIESG relationship.

In order to overcome the possible endogeneity issues due to reverse causality or the so-called omitted variable bias, we used instrumental variable regression to capitalize on two-stage least squares estimation. The instrumental variable method took advantage of the exogenous change in the implementation of XAI due to the geographical location of the research and technology-skilled workforce which met the relevance test by strongly predicting XAI adoption and plausibly met the exclusion restriction by only influencing the primary performance of the ESG due to their role in changing the implementation of XAI. In the initial stage, a regression that approximated XAI implementation as an instrument variable and control, was performed:

$$XAIit = \pi 0 + \pi 1Zit + \pi 2Xit + \upsilon it \tag{6}$$

Z it is the vector of instrumental variables. The regression of ESG performance was later realized at stage two as a predictive of the XAI implementation values of the first stage. Instrument validity also was evaluated using statistical test variables such as Cragg-Donald Wald F-statistic of instrument relevance and the Hansen J-statistic of overidentification restrictions as instruments are multichanneled.

*2.3 Machine Learning with Classification Analysis.*

In addition to customary econometric methods, we also used machine learning classification model to determine patterns that characterized high-performing organizations that have effectively used XAI technologies to improve their sustainability compared to lower-performing organizations that do not realize significant ESF improvements despite adopting XAI technologies. The analysis applied the random forest classification algorithms that were trained on predicting the ESG performance category of an organization relying on the attributes of XAI implementation, organizational attributes, and environmental influences. Random forest approach has multiple pluses such as resistance to outliers, its ability to detect nonlinear relationships and multifaceted interactions and resistance to over-fitting due to ensemble averaging which is a combination of decision trees.

This classification algorithm received a 70 percent random selection of observations which was utilized as training and the rest of the 30 percent was used during out-of-sample validation testing. The overall classification accuracy, precision and recall of each of the performance categories, F1 scores that trade-off precision-recall, and the area under the receiver operating characteristic curve that represents discrimination ability in different classification thresholds were among the metrics that were used in model performance assessment. The analysis of feature importance was used to measure how various predictor variables would explain the difference between successful and unsuccessful efforts in XAI-ESG integration, giving information on the field of predictor variables that contributed most to the accuracy of the feasibility of those undertakings.

The mathematical model of the random forest classifier combines predictions of m single decision trees, and the classifying result of this group is resolved by the voting of the majority. Given a feature vector of the observation and a given observation x the prediction can be stated as:

$$\hat{y} = mode\{h^1(x), h^2(x), \ldots, h_{\mathrm{m}}(x)\} \tag{7}$$

## 3. Results and Discussion

In this section, we provide detailed empirical evidence of our longitudinal research study on the relationship, which exists between explainable implementation of artificial intelligence and ESG performance in organizations. We give a structure to the results presentation by our analytical flow that includes descriptive statistics and the correlation analysis and then results of structural equation modeling and hierarchical regression and finally machine learning classification. During the discussion, we explain the findings according to the theoretical framework and available literature as well as emphasize the practical implications on the concept of organization sustainability management. The initial analysis involves the use of descriptive statistics to give the user an overview of the data.

### *3.1 Descriptive Statistics and Preliminary Analysis*

Table 1 can be discussed as the descriptive statistics and correlation coefficients of all the main research variables assessed in the organizations throughout the period of the observation. The sample had high differences on both the evaluation of the intensity of XAI implementation and the final results of ESG performance with the range of XAI implementation scores on the seven-point scale of 1.2-6.8 and the composite ESG scores on the scale of 100 being 34.7 to 91.3. This heterogeneity ensures there is sufficient heterogeneity in exploring the relationship between the variables given that the distributions are close to being normal and that therefore the use of parametric statistical methods is valid.

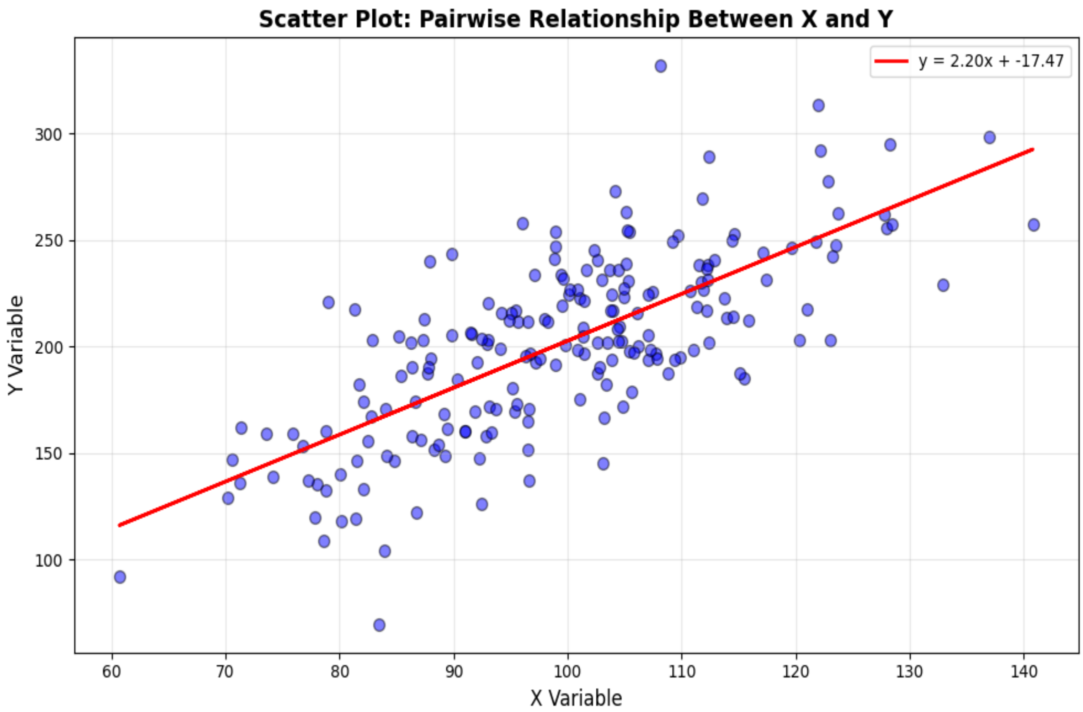


**Fig 1:** Scatter Plot with Regression Line

Analysis of correlation also found some interesting trends that were in line with the theory. The intensity of XAI implementation was shown to have a significant positive correlation with all the ESG performance dimensions at a correlation of between 0.42 and 0.51 significant at p less than 0.001. In these preliminary associations, it can be established with some initial support that the hypothesized relationships will be supported, as well as point to the fact that the environmental dimensions can be particularly sensitive towards XAI implementation. The relationships of control variables were expected, as the firm size had a positive correlation with the ESG performance, which can be explained by the resource availability reasoning, and research and development intensity had a close correlation with the use of XAI and the achievement of sustainability, which may be explained by the factor of innovation orientation.

Table 1: Descriptive Statistics for Key Study Variables

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| Composite ESG Score | 64.23 | 12.48 | 34.70 | 91.30 |
| Environmental Performance | 62.87 | 14.92 | 28.40 | 94.60 |
| Social Performance | 66.14 | 11.73 | 38.20 | 89.70 |
| Governance Performance | 63.68 | 13.26 | 31.90 | 92.40 |
| XAI Implementation | 4.17 | 1.34 | 1.20 | 6.80 |
| Firm Size (log assets) | 9.73 | 1.86 | 6.21 | 13.45 |

| | | | | |
|---|---|---|---|---|
| R&D Intensity (%) | 3.84 | 2.17 | 0.30 | 12.60 |

*3.2 Structural Equation Modeling Results*

Our fundamental assumption that the implementation of XAI can lead to organizational performance improvement in terms of ESG significantly and with several mediating processes. The model fitted the data very well with chi-square of 847.23, 312 degrees of freedom, comparative-fit index of 0.956, Tucker-Lewis index of 0.948, root mean square error of approximation of 0.041 and standardized root mean square residual of 0.038, all of which are higher than the traditional values that indicate the validation of acceptable model fit. The fit indices are evidence that the theoretical model postulated is suitable in depicting relationships among the constructs in the data.

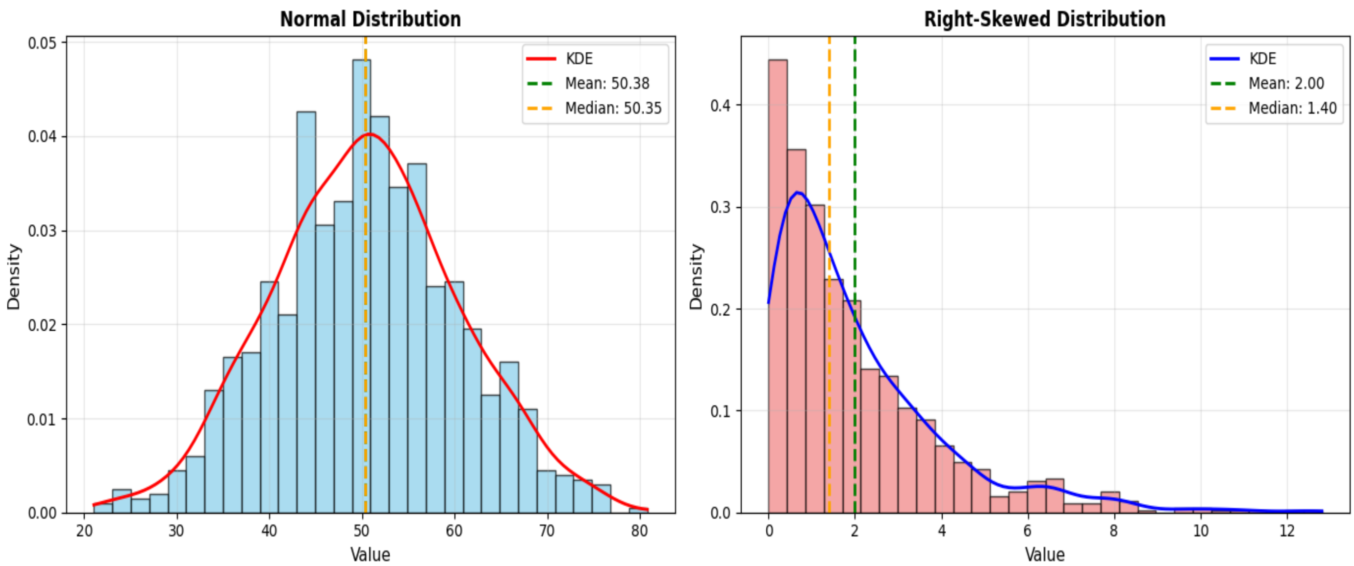


**Fig 2:** Histogram with kernel density estimate

Direct relationship between XAI implementation and composite ESG performance provided a standard coefficient of 0.387 and statistically significant at p less than 0.001 meaning that each standard deviation change in the implementation intensity of XAI would lead to the overall enhancement of ESG performance by 0.387 standard deviations. This large-sized effect is an indication of the practical importance of XAI implementation on sustainability performance. The analysis of individual ESG dimension has indicated that each of them was being differentially impacted with the strongest impact of the implementation of XAI with a standardized coefficient of 0.436 that reflected on environmental performance, governance performance and finally social performance with a significant critical value of less than 0.001. These trends indicate that the XAI technologies can prove to be especially useful in the field of environmental monitoring and optimization solutions where objective measurements and data-oriented decision making can be an obvious benefit.

Mediating mechanisms had also been analyzed and the effects of XAI implementation were found to work significantly using three primary pathways. Firstly, XAI clarity contributed to a great deal of stakeholder confidence, where the path coefficient value is 0.418 which further projected strongly the ESG performance coefficient 0.324. These summative indirect effects through stakeholder trust equated to 0.135 which represents about 35 percent of the overall XAI implementation effect. Second, the XAI implementation increased the quality of organizational decisions with coefficient of 0.392 that further increased the ESG outcomes with coefficient of 0.287 and produced indirect effect of 0.112 or 29 percent of overall effect. Third, the coefficient of 0.366 through XAI capabilities made organizational learning processes, which enhanced ESG performance with coefficient of 0.254 and created an indirect effect of 0.093 or 24 percent of total effect. Such mediating paths all explained 88 percent of the total effects of XAI on the ESG performance and just 12 percent worked by means of unmeasured direct mechanisms showing how significant all these transparency-enabled processes are.

Table 2: Structural Equation Modeling Results - Path Coefficients

| Path | Standardized Coefficient | Standard Error | t-value | p-value |
|---|---|---|---|---|
| XAI → Composite ESG | 0.387 | 0.042 | 9.214 | <0.001 |
| XAI → Environmental | 0.436 | 0.047 | 9.277 | <0.001 |
| XAI → Social | 0.329 | 0.044 | 7.477 | <0.001 |
| XAI → Governance | 0.361 | 0.045 | 8.022 | <0.001 |
| XAI → Trust | 0.418 | 0.046 | 9.087 | <0.001 |
| Trust → ESG | 0.324 | 0.041 | 7.902 | <0.001 |
| XAI → Decision Quality | 0.392 | 0.043 | 9.116 | <0.001 |
| Decision Quality → ESG | 0.287 | 0.039 | 7.359 | <0.001 |

### *3.3 Hierarchy Regression and Moderating Effects.*

Table 3 of hierarchical regression findings supports the findings of structural equation modeling with further trends of moderating factors that influence the XAI-ESG relationship. Model 1 forms baseline relationships with only firm and industry attributes which reveal that firm size is a positive predictor with a coefficient of 2.847, research and development intensity is positively associated with a coefficient of 1.923 mainly, and the profitability is having a moderate positive impact with a coefficient of 0.672 which have significance levels met traditional standards. The effect of the industry significantly contributes to the variance strengthened by technology, financial services, and the healthcare industry whose ESG score appears higher compared to manufacturing base category.

Model 2 reveals the implementation variable of the XAI that shows a very significant positive coefficient of 4.183 that a one-point increase in the XAI implementation seven-point scale would be correlated with a 4.183-point increase in the composite ESG scores. It is also strong following the adjustment of all firm and industry factors and the XAI variable alone depicts an extra 18.7 percent of the variance in comparison with the baseline model as indicated by the increment in the R-squared of 0.327 in Model 1 in 0.514 in Model 2. The scale of this effect can be extrapolated to imply a significant practical effect, which forecasts that the organizations shifting in the direction of high XAI implementing intensity, may anticipate enhancing the composite scores of ESG by more than 23 points, which means almost a full standard deviation increase.

The Model 3 analyzes the moderation effect by adding interaction terms between the implementation of the XAI and prominent organization and environmental attributes. The relationship between XAI implementation and regulatory intensity shows a significant positive coefficient of 1.847, which shows that the XAI benefits on the performance increase significantly when the regulatory segment is highly regulated and compliance and stakeholder probing are high, hence putting pressure on the operation of the company to maintain transparency. On the other hand, the relationship between the implementation of XAI and organizational complexity is negative with a negative coefficient of -0.923 which implies that the benefits will decrease slightly in high organizational structure where it is more difficult to coordinate XAI implementation across various units and achieve uniform implementation implementation of XAI. The two-tailed correlation between XAI implementation and the maturity of the digital transformation is positive (2.134) which indicates a complementary nature between the XAI capabilities and the already established digital infrastructure whereby the more mature the base technological capabilities of an organization, the more value it acquires with XAI investments.

Table 3: Hierarchical Regression Results for Composite ESG Performance

| Variable | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Constant | 34.267*** | 21.483*** | 19.742*** |
| Firm Size | 2.847*** | 2.164*** | 2.093*** |
| R&D Intensity | 1.923*** | 1.347** | 1.289** |
| Profitability | 0.672** | 0.514* | 0.487* |
| XAI Implementation | - | 4.183*** | 4.067*** |
| XAI × Regulatory Intensity | - | - | 1.847** |
| XAI × Org Complexity | - | - | -0.923* |
| XAI × Digital Maturity | - | - | 2.134*** |
| $R^2$ | 0.327 | 0.514 | 0.562 |
| Adjusted $R^2$ | 0.319 | 0.508 | 0.554 |
| F-statistic | 42.87*** | 78.34*** | 67.92*** |

*Note: *** p<0.001, ** p<0.01, * p<0.05. Industry and time fixed effects included in all models.*

*3.4 Instrumental Variable Analysis and Causality*

In order to counter endogeneity issues and reinforce causal relationships, we applied the instrumental variable regression, two stage least squares estimation. According to the first-step regression findings (Table 4), there is high predictive ability of our instrumental variables on XAI implementation. Geographic distance to AI research centres, i.e., the inverse distance to the closest top-ranked university that has active research teaching AI technologies, has a significant positive coefficient of 0.284, with the implication that organisations based in closer proximity to AI innovation centres embrace XAI technologies to a greater extent. The presence of AI-skilled workers in the region, as a metric to AI implementation predictors, the concentration of information scientists and machine learning engineers (kper thousand workers in the metropolitan region) is also statistically significant in predicting XAI with a field of 0.317. The combination of these instruments is used to explain significant variation in the XAI adoption, and the F-statistic of the first stage is 87.43, which is dramatically higher than the traditional 10 cut-off of instrument strength and thus strong instruments are not going to be of a problem.

The second-stage result with the use of the implementation values of predicted XAI results generates an estimated effect on composite ESG performance of 5.127, which is considerably large as compared to the ordinary least squares coefficient of 4.183, indicating that failure to account endogeneity bias results in an employment of downward estimates. The practice suggests that the organizations with less intrinsic sustainability performance propensity are possibly more likely to use XAI technologies as a corrective action, which results in negative selection and mitigates any effects of non-instrumental methods. The Hansen J-statistic measures of overidentification restrictions condition is 2.847 (p=0.241), which does not reject the null hypothesis of instrument validity and takes the view in favour of the assumption of the exclusion restriction. These instrumental results of the variables greatly qualify the belief in causation of interpretation of XAI implementation effects on ESG performance.

Table 4: Instrumental Variable Regression Results

| Variable | First Stage (XAI Implementation) | Second Stage (ESG Performance) |
|---|---|---|
| Proximity to AI Research Centers | 0.284*** (0.037) | - |
| AI-Skilled Labor Density | 0.317*** (0.041) | - |
| Predicted XAI Implementation | - | 5.127*** (0.724) |
| Controls Included | Yes | Yes |
| First-Stage F-statistic | 87.43 | - |
| Hansen J-statistic (p-value) | - | 2.847 (0.241) |
| Observations | 9,336 | 9,336 |

*Note: Standard errors in parentheses. *** p<0.001. Controls include firm size, R&D intensity, profitability, leverage, industry and time fixed effects.*

### *3.5 Machine Learning Classification Results*

Random forest classification analysis can be used to compliment insights since it offers new features of organizational and implementation characteristics that characterize the high ESG achievers as effectively utilizing XAI capabilities over those with lower results that see little sustainability returns despite having XAI operational. This gave three categories of performance based on improvements in ESG scores after implementation of the XAI with high performers having an improvement more than a standard deviation above the mean, moderate performers having an improvement of between zero and one standard deviation above the mean and low performers having an improvement below the mean. The classification algorithm which had been trained on 70 percent of the observations had a general accuracy of 81.3 percent on the reserved validation set which is significantly higher than the accuracy of 33.3 percent due to random guessing, proving there was useful predictive information indeed.

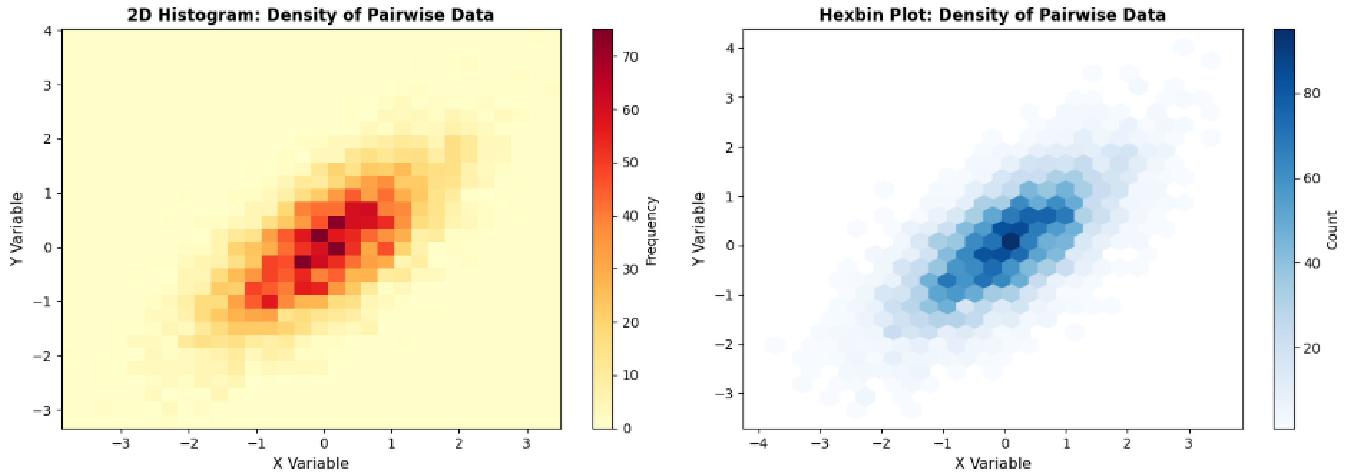


**Fig 3:** 2D histogram and hexbin plot

The performance metrics of Table 5 are a detailed classification performance by the three classes of performance. Precision among high performers was determined to be 0.847 and this implies that 84.7 percent of the high performers that were actually high performers actually succeeded in making better improvements in regard to ESG, whereas recall of 0.793 shows that the model has done a good job in the identification of high performers which were actually high. F1 scores that balance the measurement between accuracy and recall comprised of high, low, and moderate performers, which are 0.819, 0.726, and 0.798, respectively, with the negative value of the latter indicating more heterogeneity in the lower-ranking group of organizations with less XAI benefits. The region below the receiver operating characteristic curve was an average of 0.887 in the three categories, which illustrates high discrimination ability and proves that there is good ability of the model to be used to neatly differentiate between the levels of performance based on the predictor variables.

Analysis of the importance of the features showed that the implementation sophistication of XAI became the only most important variable with the normalized importance score of 0.287 significantly higher than the rest of the variables. The result confirms that the effectiveness and depth of XAI implementation is more relevant than adoption breadth in order to realize an improvement in sustainability performance. The stakeholder engagement intensity had the second-largest importance score (0.194), indicating the need to take the involved stakeholders actively and not view transparency as the technical issue when designing and implementing the XAI system. Organization learning culture ranked as the third with the score of 0.173 implying that organizations have to develop environments that will sustain knowledge creation and sharing to entirely leverage knowledge that is created using XAI systems. The fourth most important characteristic was the digital infrastructure maturity with a value of 0.142, then senior leadership commitment which had the value of 0.118, then cross-functional integration had the value of 0.086, and other organizational characteristics that had values under 0.080 have importance scores.

Table 5: Random Forest Classification Performance Metrics

| Performance Category | Precision | Recall | F1 Score | AUC-ROC |
|---|---|---|---|---|
| High ESG Performers | 0.847 | 0.793 | 0.819 | 0.912 |
| Moderate ESG Performers | 0.789 | 0.807 | 0.798 | 0.876 |
| Low ESG Performers | 0.714 | 0.738 | 0.726 | 0.873 |
| **Weighted Average** | **0.783** | **0.779** | **0.781** | **0.887** |
| **Overall Accuracy** | | | **81.3%** | |

3.6 Discussion and Theoretical implications.

The empirical results above give a strong support on our main theoretical hypothesis that explainable artificial intelligence implementation plays an important role in improving the organizational ESG performance through transparency-enhancing mechanisms that can develop stakeholder trust, increase quality of decision and learn organizationally [49-50]. Such findings contribute to various significant theoretical findings that push the academic knowledge on the concept of technology-sustainability intersections and frames new research directions on future investigations [51,52]. To begin with, our results form an extension of the stakeholder theory; that is, we show that algorithmic transparency is an essential tool in a rapidly-digitizing organization to obtain and sustain stakeholder faith [53-56]. Although the traditional theory of stakeholders focuses on the interpersonal communication channels and relationship management practices, our data indicate that transparency in automated decision systems is also an equally significant factor that adversely affect stakeholder perceptions and behaviors as organizations using AI technologies in their main operations [57-58].

The extensive mediation of XAI effects via the stakeholder trust mediation channels confirms that transparency is not only a technical feature of AI systems but also a strategic requirement of the organization that can influence the essence of relationships between the key stakeholders [6,60-61]. The effective implementation of XAI technologies by organizations makes their automated decision-making processes understandable to their various stakeholders such as investors, customers, employees, regulators and civil society organisations and thus show accountability and provides informed engagement. Such transparency eliminates the information asymmetry which in turn erodes stakeholder trust in organizational sustainability obligations especially when the concerned stakeholders are not trained in technical aspects to assess the sophisticated AI systems on their own. The existence of stakeholder trust in mediating between all XAI effects on ESG performance spares the fact that the opportunity to specifically frame XAI implementations in such a way that stakeholder understanding needs are considered is of practical significance instead of viewing transparency as merely an internal technical obligation.

Second, our outcomes add to the perspectives of resource-based view by modeling the XAI capabilities as the unique organizational resources capable of cultivating sustainable competitive advantages by the effects they have on the quality of decisions and organizational learning. The RBV model puts stress on the fact that competitive advantages are created by resources that are valuable, rare, inimitable, and not substitutable. The capabilities of XAI meet these requirements as they allow companies to get high-end insights based on sustainability data, ensure better strategic decisions based on environmental and social investments, and ensure knowledge building better by using transparent analysis of previous decisions. The report that mediated effects of XAI are equivalent to 29 percent of the decision quality, validates the fact that transparency has a positive impact on organizational outcomes by not only providing condition to facilitate the relationship of external stakeholders but also improving the establishment of superior internal decision-making practices. By becoming familiar with the way AI systems provide the recommendations concerning the potential strategies to reduce the emissions or coordinate the supply chain adjustments or concentrate on the community investment areas, sustainability managers would find it easier to combine the information offered by the algorithm with the contextual knowledge and the opinions of the stakeholders to achieve better-informed decisions.

Moreover, the mediation (24 percent) of all effects by organizational learning mechanisms provides emphasis on the role of XAI capabilities in developing dynamic but not fixed competitive advantages.

Open AI systems facilitate organizations to systematize the analysis of why certain sustainability projects performed (or did not), causal mechanisms that may relate activities with the results, and learn, which can inform decision-making in the future. This advantage based on learning is especially sustainable in the sense that, it enhances the organization capabilities in the long run as opposed to performance enhancement which can be achieved one time only. Companies that adopt XAI technologies are capable of creating better organizational intelligence concerning sustainability processes that cannot be easily achieved by rivals in the context of the mere technology-buying process since the acquired knowledge disseminates within the organizational routine, culture, and human capital. Third, our moderating effect tests reflect favourable boundary conditions that inform the XAI-ESG relationship and also point to situations in which organisations should factor in contextual factors in adopting these technologies. The regulatory strength moderation has a positive effect, which validates the hypothesis that XAI gains obtain substantial growth in highly regulated sectors where disclosure helps to show compliance and allows organizations to meet the complicated regulation demands more efficiently. This tendency indicates that regulatory pressures are not only limiting factors but also promoters of the returns on the investments in transparency because they arouse the demand of stakeholders on the organizations to act responsibly and provide competitive advantages to organizations that surpass the minimum compliance requirements. On the other hand, the negative moderation of the organizational complexity implies that the XAI implementation issues are heightened in organizations of structure complexities where coordinating the technology implementation effort among various business units, ensuring the uniformity of practices, and integrating the systems among them is more challenging.

It can be seen that the moderation between digital transformation maturity is positive, indicating the existence of significant complementarities between the XAI capabilities and the current technology infrastructure in the organization. Companies with higher level of underlying digital capacity derive higher value out of XAI investment due to better data quality, higher analytics architecture and capability of more efficient XAI implementation and use. This synergistic aspect implies that the adoption of XAI can be considered as one of the constituent elements of more broad-based digital transformation pathways, and that the greatest benefits will go to the organizations that will ultimately incorporate XAI technologies into the wider digital strategies. The result also presupposes the possibility of the further increase in performance disparities between digitally forward and backward organizations as the former achieve better returns on investments in sustainability technologies.

Fourth, the machine learning classification outcomes will offer innovative understanding of organizational and implementation features that can reveal a difference between successful XAI implementation and unsuccessful attempts. The superiority that implementation sophistication has on adoption breadth as compared to implementation sophistication in predicting improvements in ESG performance prove that depth plays a more significant role than breadth in implementation of XAI. Any organization can attain better sustainability results not in terms of XAI technologies implemented in as many domains of functioning as possible but with quality, high-end implementations that actually increase transparency and allow interacting with stakeholders. This observation questions the views of the technology diffusion about the perceptions based on adoption level as the main measure of success but rather seems to implement quality the key measure of success of realising technology gains. The fact that the stakeholder engagement intensity and organizational learning culture were among the top-ranked features of importance once again proves that successful XAI adoption means the presence of organizational capabilities and practice that should be supplemented by technical ones.

## 4. Conclusion

The study contributes greatly to the new research areas that study the interface of artificial intelligence technology and corporate sustainability because it formulates and empirically verifies a comprehensive theoretical expectation connecting explainable AI implementation with ESG performance of organisations. Based on longitudinal data on multinational companies across various industries and using several complementary methods of analysis such as structural equation modeling, hierarchical regression analysis, instrumental variable estimation, and machine learning classification, we find that

XAI adoption produces large improvements in environmental, social, and governance performance. These impacts work mainly via the mechanisms of transparency that promote stakeholder credibility, better the quality of decision making and organizational learning criteria and the environmental performance dimensions portray a particularly worthwhile stock of responsiveness to XAI practice.

The results obtained with our findings have a number of significant theoretical implications that contribute to the development of the scholarship and define such new research directions. To start with, we enlarge the scope of stakeholder theory by proving that algorithmic transparency is an important mechanism of creating stakeholder trust in the organizational relationship mediating technology to supplement the traditional focus on interpersonal communication channels. Second, we add to the perspectives of the resource-based views, when defining XAI capabilities as unique organizational resources creating sustainable competitive advantages due to their influence on the quality of decisions and learning in organizations. Third, we identify significant boundary conditions such as regulatory strength, organizational endowment, and maturity of digital transformation which mediate XAI implications and emphasis on situation factors to be addressed by the organization adopting such technologies.

To contribute to the managerial practice, our study can offer evidence-based work to organizations that want to use XAI technologies to improve sustainability performance. The results verify that XAI is a practical and strategic strategy in terms of its effect that can be used to enhance ESG performance. Nonetheless, to be adopted successfully, implementation quality instead of the breadth of deployment must be noted, and sophisticated and well-structured systems providing a meaningful impact on the increase of transparency and stakeholder feedback are the most efficient ones. Organizations need to be keen on stakeholder engagement both during XAI design and deployment engagements, develop cultures based on a form of learning to make proper use of transparency-based insights, and have a sufficient level of digital infrastructure maturity before engaging in significant XAI investing. The organizations with a well-regulated sector or those with a high level of digital capabilities should be aware of the highest potential returns in the XAI investments.

Nonetheless, this research has a number of limitations that indicate possible employment of new avenues of research in the future. First, our instrumental variable method enhances the causal inferences, but quasi-experimental or experimental designs would give a more conclusive stance on the impact of XAI on the work of ESG. Subsequent studies of the kind may exploit natural experiments due to change of regulation, technology shock or other exogenous occurrences to more definitively find causality. Second, the intensity of implementation of XAI is measured by self-reported organization-level surveys, which is further validated by archival research, but more detailed technical audits of the actual XAI system capabilities would allow a deeper insight into what exactly about the XAI system techniques and features were the processes of sustainability improvement. Future research may use in technical measures such as looking at the mechanism of generating the explanations, accessibility by stakeholders, and integration with the decision processes.

Third, our sample represents a wide range of industries and geographies; however, it will be concentrated in the developed Western economies with well-developed sustainability reporting systems and in already established markets of AI. Future studies ought to research XAI-ESG associations in newer markets with institutionalized setting, policies, expectations of stakeholders and technological potentials. These extensions would be a test of the generalizability of our findings as well as attempt to discover context-specific mechanisms and boundary conditions. Fourth, the four years of observation can imply medium-term XAI impacts but cannot investigate long-term dynamics, such as conceivable performance leveling, obsolescence, or changing stakeholder anticipations. The longitudinal studies that are long-term, over five years, would be helpful in understanding the sustainability of the performance improvements that are brought about by XAI and whether the benefits are maintained, decline or increase as time passes.

Fifth, although we find stakeholder trust, decision quality and organizational learning as important mediating variables, there are other plausible pathways that may act out in mediation and explanation of the XAI impacts on ESG performance. Such mechanisms as improved regulatory compliance, greater risk management, stronger corporate reputation, and employee engagement improvement can be investigated in the future research. Sixth, the fact that we focused on the company level results does not help us understand the impact of the XAI implementation among various stakeholder groups on them differently. Subsequent research would be conducted to determine the effects of XAI on individual groups of stakeholders such as investors, customers, employees, suppliers, local communities, and civil society organizations and assess whether transparency will affect a group of stakeholders more than others and find possible tensions or trade-offs.

Seventh, there is a fast technological progression towards implying that in the coming years, there are still more changes to come in the XAI capabilities, techniques, and applications. The recent advancements in technology should be monitored in future studies and how new XAI technologies can impact the sustainability outcomes in a different manner than the existing ones. There should be specific focus on the effect of foundation models, multimodal AI systems and enhanced neural architecture search algorithms on the effectiveness of XAI implementations. Eighth, as we are considering the XAI effects on the ESG performance in general, it would be interesting to explore the mechanisms associated with transparency and its particular sustainability implications more closely. Future studies may look at the impact of the implementation of XAI on specific aspects of the environment, e.g., carbon emissions and water usage, biodiversity concerns, or social aspects, e.g., diversity and social inclusion, labor rights, and involvement of communities.

This study shows that explainable artificial intelligence is a prospective area in technology where organizations look to improve their sustainability performance in addition to overcoming the lack of transparency that are characteristic of traditional AI applications. With organizations overgrowing demands both to innovate in a technological aspect and towards environmental and social responsibility, XAI technologies provide mechanisms to follow these goals and pursue them synergistically and not as competing priorities. Making the algorithmic decision-making processes understandable to various stakeholders, XAI implementations can enhance the sustainability outcomes at once, while also enhancing trust relations on which long-term organizational legitimacy is based on. The organizations that assume XAI as an organizational strategic ability and not a technical need will be enabled to achieve significant competitive benefits in a more sustainability-oriented global economy. In the future, the areas of research, practice innovation, and the policy development will be crucial to enable the full potential of XAI technologies to become visible and help to solve the acute challenges faced by the contemporary society regarding its sustainability on the corporate level and due to the current challenging environmental and social issues.

**Author Contributions**

AP: Conceptualization, methodology, writing original draft, writing review and editing, and supervision. NLR: Study design, analysis, data collection, visualization, writing original draft, writing review and editing, and supervision. JR: Data collection, methodology, visualization, writing original draft, writing review and editing, and supervision.

**Conflict of interest**

The authors declare no conflicts of interest.

## References

[1] Schneider J, Abraham R, Meske C, Vom Brocke J. Artificial intelligence governance for businesses. Information Systems Management. 2023 Jul 3;40(3):229-49. https://doi.org/10.1080/10580530.2022.2085825

[2] Sandeep SR, Ahamad S, Saxena D, Srivastava K, Jaiswal S, Bora A. To understand the relationship between Machine learning and Artificial intelligence in large and diversified business organisations. Materials Today: Proceedings. 2022 Jan 1;56:2082-6. https://doi.org/10.1016/j.matpr.2021.11.409

[3] Verma C, Vijayalakshmi P, Chaturvedi N, Umesh U, Rai A, Ahmad AY. Artificial Intelligence in Marketing Management: Enhancing Customer Engagement and Personalization. In2025 International Conference on Pervasive Computational Technologies (ICPCT) 2025 Feb 8 (pp. 397-401). IEEE. https://doi.org/10.1109/ICPCT64145.2025.10940626

[4] Chen J, Lim CP, Tan KH, Govindan K, Kumar A. Artificial intelligence-based human-centric decision support framework: an application to predictive maintenance in asset management under pandemic environments. Annals of Operations Research. 2025 Jul;350(2):493-516. https://doi.org/10.1007/s10479-021-04373-w

[5] Storey VC, Yue WT, Zhao JL, Lukyanenko R. Generative artificial intelligence: Evolving technology, growing societal impact, and opportunities for information systems research. Information Systems Frontiers. 2025 Feb 25:1-22.

[6] Wamba-Taguimdje SL, Fosso Wamba S, Kala Kamdjoug JR, Tchatchouang Wanko CE. Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Business process management journal. 2020 Nov 2;26(7):1893-924. https://doi.org/10.1108/BPMJ-10-2019-0411

[7] Svetlana N, Anna N, Svetlana M, Tatiana G, Olga M. Artificial intelligence as a driver of business process transformation. Procedia Computer Science. 2022 Jan 1;213:276-84. https://doi.org/10.1016/j.procs.2022.11.067

[8] Xu JJ, Babaian T. Artificial intelligence in business curriculum: The pedagogy and learning outcomes. The International Journal of Management Education. 2021 Nov 1;19(3):100550. https://doi.org/10.1016/j.ijme.2021.100550

[9] Maslak OI, Maslak MV, Grishko NY, Hlazunova OO, Pererva PG, Yakovenko YY. Artificial intelligence as a key driver of business operations transformation in the conditions of the digital economy. In2021 IEEE International Conference on Modern Electrical and Energy Systems (MEES) 2021 Sep 21 (pp. 1-5). IEEE. https://doi.org/10.1109/MEES52427.2021.9598744

[10] Reier Forradellas RF, Garay Gallastegui LM. Digital transformation and artificial intelligence applied to business: Legal regulations, economic impact and perspective. Laws. 2021 Aug 27;10(3):70. https://doi.org/10.3390/laws10030070

[11] Ahmed AA, Agarwal S, Kurniawan IG, Anantadjaya SP, Krishnan C. Business boosting through sentiment analysis using Artificial Intelligence approach. International Journal of System Assurance Engineering and Management. 2022 Mar;13(Suppl 1):699-709. https://doi.org/10.1007/s13198-021-01594-x

[12] Kanbach DK, Heiduk L, Blueher G, Schreiter M, Lahmann A. The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. Review of Managerial Science. 2024 Apr;18(4):1189-220. https://doi.org/10.1007/s11846-023-00696-z

[13] Kumar S, Lim WM, Sivarajah U, Kaur J. Artificial intelligence and blockchain integration in business: trends from a bibliometric-content analysis. Information systems frontiers. 2023 Apr;25(2):871-96. https://doi.org/10.1007/s10796-022-10279-0

[14] Chowdhury S, Budhwar P, Wood G. Generative artificial intelligence in business: towards a strategic human resource management framework. British Journal of Management. 2024 Oct;35(4):1680-91. https://doi.org/10.1111/1467-8551.12824

[15] Mishra AN, Pani AK. Business value appropriation roadmap for artificial intelligence. VINE Journal of Information and Knowledge Management Systems. 2021 May 31;51(3):353-68. https://doi.org/10.1108/VJIKMS-07-2019-0107

[16] Beheshti A, Yang J, Sheng QZ, Benatallah B, Casati F, Dustdar S, Nezhad HR, Zhang X, Xue S. ProcessGPT: transforming business process management with generative artificial intelligence. In2023 IEEE international conference on web services (ICWS) 2023 Jul 2 (pp. 731-739). IEEE. https://doi.org/10.1109/ICWS60048.2023.00099

[17] Vardarlier P, Zafer C. Use of artificial intelligence as business strategy in recruitment process and social perspective. InDigital business strategies in blockchain ecosystems: Transformational design and future of global business 2019 Nov 10 (pp. 355-373). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-29739-8_17

[18] Agarwal P, Swami S, Malhotra SK. Artificial intelligence adoption in the post COVID-19 new-normal and role of smart technologies in transforming business: a review. Journal of Science and Technology Policy Management. 2024 Apr 18;15(3):506-29. https://doi.org/10.1108/JSTPM-08-2021-0122

[19] Kar AK, Kushwaha AK. Facilitators and barriers of artificial intelligence adoption in business-insights from opinions using big data analytics. Information Systems Frontiers. 2023 Aug;25(4):1351-74. https://doi.org/10.1007/s10796-021-10219-4

[20] Alawadhi SA, Zowayed A, Abdulla H, Khder MA, Ali BJ. Impact of artificial intelligence on information security in business. In2022 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS) 2022 Jun 22 (pp. 437-442). IEEE. https://doi.org/10.1109/ICETSIS55481.2022.9888871

[21] Sjödin D, Parida V, Kohtamäki M. Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. Technological Forecasting and Social Change. 2023 Dec 1;197:122903. https://doi.org/10.1016/j.techfore.2023.122903

[22] Davenport TH, Ronanki R. Artificial intelligence for the real world. Harvard business review. 2018 Jan 1;96(1):108-16.

[23] Abrokwah-Larbi K, Awuku-Larbi Y. The impact of artificial intelligence in marketing on the performance of business organizations: evidence from SMEs in an emerging economy. Journal of Entrepreneurship in Emerging Economies. 2024 Jun 13;16(4):1090-117. https://doi.org/10.1108/JEEE-07-2022-0207

[24] Almaraz-López C, Almaraz-Menéndez F, López-Esteban C. Comparative study of the attitudes and perceptions of university students in business administration and management and in education toward artificial intelligence. Education Sciences. 2023 Jun 15;13(6):609. https://doi.org/10.3390/educsci13060609

[25] Haenlein M, Huang MH, Kaplan A. Guest editorial: Business ethics in the era of artificial intelligence. Journal of Business Ethics. 2022 Jul;178(4):867-9. https://doi.org/10.1007/s10551-022-05060-x

[26] Di Vaio A, Palladino R, Hassan R, Escobar O. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. Journal of Business Research. 2020 Dec 1;121:283-314. https://doi.org/10.1016/j.jbusres.2020.08.019

[27] Oldemeyer L, Jede A, Teuteberg F. Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. Management Review Quarterly. 2025 Jun;75(2):1185-227. https://doi.org/10.1007/s11301-024-00405-4

[28] Kerzel U. Enterprise AI Canvas Integrating artificial intelligence into business. Applied Artificial Intelligence. 2021 Jan 2;35(1):1-2. https://doi.org/10.1080/08839514.2020.1826146

[29] Singh S, Goyal MK. Enhancing climate resilience in businesses: the role of artificial intelligence. Journal of Cleaner Production. 2023 Sep 15;418:138228. https://doi.org/10.1016/j.jclepro.2023.138228

[30] Shwedeh F, Alzoubi HM. Creating and Evaluating Instructional Java Programming Codes with Utilization of Artificial Intelligence for Customized Business Requirements. InInternational Scientific Conference Management and Engineering 2024 Jun 23 (pp. 281-286). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-89889-1_31

[31] Toniolo K, Masiero E, Massaro M, Bagnoli C. Sustainable business models and artificial intelligence: Opportunities and challenges. Knowledge, people, and digital transformation: Approaches for a sustainable future. 2020 Apr 23:103-17. https://doi.org/10.1007/978-3-030-40390-4_8

[32] Kulkov I. Next-generation business models for artificial intelligence start-ups in the healthcare industry. International Journal of Entrepreneurial Behavior & Research. 2023 May 4;29(4):860-85. https://doi.org/10.1108/IJEBR-04-2021-0304

[33] Rana NP, Chatterjee S, Dwivedi YK, Akter S. Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness. European Journal of Information Systems. 2022 May 4;31(3):364-87. https://doi.org/10.1080/0960085X.2021.1955628

[34] Jorzik P, Yigit A, Kanbach DK, Kraus S, Dabić M. Artificial intelligence-enabled business model innovation: Competencies and roles of top management. IEEE transactions on engineering management. 2023 May 24;71:7044-56. https://doi.org/10.1109/TEM.2023.3275643

[35] Kalogiannidis S, Kalfas D, Papaevangelou O, Giannarakis G, Chatzitheodoridis F. The role of artificial intelligence technology in predictive risk assessment for business continuity: A case study of Greece. Risks. 2024 Jan 23;12(2):19. https://doi.org/10.3390/risks12020019

[36] Chen R, Zhang T. Artificial intelligence applications implication for ESG performance: can digital transformation of enterprises promote sustainable development?. Chinese Management Studies. 2025 May 13;19(3):676-701. https://doi.org/10.1108/CMS-11-2023-0653

[37] Zhou X, Li G, Wang Q, Li Y, Zhou D. Artificial intelligence, corporate information governance and ESG performance: Quasi-experimental evidence from China. International Review of Financial Analysis. 2025 Jun 1;102:104087. https://doi.org/10.1016/j.irfa.2025.104087

[38] Gursoy D, Cai R. Artificial intelligence: an overview of research trends and future directions. International Journal of Contemporary Hospitality Management. 2025 Jan 2;37(1):1-7. https://doi.org/10.1108/IJCHM-03-2024-0322

[39] Shaik AS, Alshibani SM, Jain G, Gupta B, Mehrotra A. Artificial intelligence (AI)-driven strategic business model innovations in small-and medium-sized enterprises. Insights on technological and strategic enablers for carbon neutral businesses. Business Strategy and the Environment. 2024 May;33(4):2731-51. https://doi.org/10.1002/bse.3617

[40] Cavazza A, Dal Mas F, Paoloni P, Manzo M. Artificial intelligence and new business models in agriculture: a structured literature review and future research agenda. British Food Journal. 2023 Jul 12;125(13):436-61. https://doi.org/10.1108/BFJ-02-2023-0132

[41] Sahoo S, Kumar S, Donthu N, Singh AK. Artificial intelligence capabilities, open innovation, and business performance-Empirical insights from multinational B2B companies. Industrial marketing management. 2024 Feb 1;117:28-41. https://doi.org/10.1016/j.indmarman.2023.12.008

[42] Alam A, Mohanty A. Business models, business strategies, and innovations in EdTech companies: integration of learning analytics and artificial intelligence in higher education. In2022 IEEE 6th Conference on Information and Communication Technology (CICT) 2022 Nov 18 (pp. 1-6). IEEE. https://doi.org/10.1109/CICT56698.2022.9997887
[43] Jorzik P, Antonio JL, Kanbach DK, Kallmuenzer A, Kraus S. Sowing the seeds for sustainability: A business model innovation perspective on artificial intelligence in green technology startups. Technological forecasting and social change. 2024 Nov 1;208:123653. https://doi.org/10.1016/j.techfore.2024.123653
[44] Fallahi S, Mellquist AC, Mogren O, Listo Zec E, Algurén P, Hallquist L. Financing solutions for circular business models: Exploring the role of business ecosystems and artificial intelligence. Business Strategy and the Environment. 2023 Sep;32(6):3233-48. https://doi.org/10.1002/bse.3297
[45] Drydakis N. Artificial Intelligence and reduced SMEs' business risks. A dynamic capabilities analysis during the COVID-19 pandemic. Information Systems Frontiers. 2022 Aug;24(4):1223-47. https://doi.org/10.1007/s10796-022-10249-6
[46] Badghish S, Soomro YA. Artificial intelligence adoption by SMEs to achieve sustainable business performance: application of technology-organization-environment framework. Sustainability. 2024 Feb 24;16(5):1864. https://doi.org/10.3390/su16051864
[47] Hu KH, Chen FH, Hsu MF, Tzeng GH. Governance of artificial intelligence applications in a business audit via a fusion fuzzy multiple rule-based decision-making model. Financial Innovation. 2023 Aug 14;9(1):117. https://doi.org/10.1186/s40854-022-00436-4
[48] Qi B, Shen Y, Xu T. An artificial-intelligence-enabled sustainable supply chain model for B2C E-commerce business in the international trade. Technological forecasting and social change. 2023 Jun 1;191:122491. https://doi.org/10.1016/j.techfore.2023.122491
[49] Upadhyay N, Upadhyay S, Al-Debei MM, Baabdullah AM, Dwivedi YK. The influence of digital entrepreneurship and entrepreneurial orientation on intention of family businesses to adopt artificial intelligence: examining the mediating role of business innovativeness. International Journal of Entrepreneurial Behavior & Research. 2023 Jan 17;29(1):80-115. https://doi.org/10.1108/IJEBR-02-2022-0154
[50] Abdelwahab HR, Rauf A, Chen D. Business students' perceptions of Dutch higher educational institutions in preparing them for artificial intelligence work environments. Industry and Higher Education. 2023 Feb;37(1):22-34. https://doi.org/10.1177/09504222221087614
[51] Bickley SJ, Macintyre A, Torgler B. Artificial intelligence and big data in sustainable entrepreneurship. Journal of Economic Surveys. 2025 Feb;39(1):103-45. https://doi.org/10.1111/joes.12611
[52] Demaidi MN. Artificial intelligence national strategy in a developing country. Ai & Society. 2025 Feb;40(2):423-35. https://doi.org/10.1007/s00146-023-01779-x
[53] Krishnan C, Gupta A, Gupta A, Singh G. Impact of artificial intelligence-based chatbots on customer engagement and business growth. InDeep learning for social media data analytics 2022 Sep 19 (pp. 195-210). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-10869-3_11
[54] Saleem I, Al-Breiki NS, Asad M. The nexus of artificial intelligence, frugal innovation and business model innovation to nurture internationalization: A survey of SME's readiness. Journal of Open Innovation: Technology, Market, and Complexity. 2024 Sep 1;10(3):100326. https://doi.org/10.1016/j.joitmc.2024.100326
[55] Met İ, Kabukçu D, Uzunoğulları G, Soyalp Ü, Dakdevir T. Transformation of business model in finance sector with artificial intelligence and robotic process automation. InDigital business strategies in blockchain ecosystems: Transformational design and future of global business 2019 Nov 10 (pp. 3-29). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-29739-8_1
[56] Fonseka K, Jaharadak AA, Raman M. Impact of E-commerce adoption on business performance of SMEs in Sri Lanka; moderating role of artificial intelligence. International Journal of Social Economics. 2022 May 16;49(10):1518-31. https://doi.org/10.1108/IJSE-12-2021-0752
[57] Lada S, Chekima B, Karim MR, Fabeil NF, Ayub MS, Amirul SM, Ansar R, Bouteraa M, Fook LM, Zaki HO. Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses. Journal of Open Innovation: Technology, Market, and Complexity. 2023 Dec 1;9(4):100144. https://doi.org/10.1016/j.joitmc.2023.100144
[58] Tavera Romero CA, Ortiz JH, Khalaf OI, Ríos Prado A. Business intelligence: business evolution after industry 4.0. Sustainability. 2021 Sep 7;13(18):10026. https://doi.org/10.3390/su131810026
[59] Amirkolaii KN, Baboli A, Shahzad MK, Tonadre R. Demand forecasting for irregular demands in business aircraft spare parts supply chains by using artificial intelligence (AI). IFAC-PapersOnLine. 2017 Jul 1;50(1):15221-6. https://doi.org/10.1016/j.ifacol.2017.08.2371

[60] Allal-Chérif O, Simón-Moya V, Ballester AC. Intelligent purchasing: How artificial intelligence can redefine the purchasing function. Journal of Business Research. 2021 Jan 1;124:69-76. https://doi.org/10.1016/j.jbusres.2020.11.050

[61] Wach K, Duong CD, Ejdys J, Kazlauskaitė R, Korzynski P, Mazurek G, Paliszkiewicz J, Ziemba E. The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. Entrepreneurial Business and Economics Review. 2023 Jun 30;11(2):7-30. https://doi.org/10.15678/EBER.2023.110201