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Integrating ESG Metrics into AI-Driven Credit Evaluation: A Multi-Dimensional Modelling Approach for Sustainable Finance

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Abstract: The transition to sustainable finance has accelerated the demand for more holistic credit evaluation frameworks that incorporate Environmental, Social, and Governance (ESG) dimensions. Traditional credit scoring models often overlook ESG-related risks and opportunities, leading to incomplete risk assessments. This study proposes a novel AI-driven multi-dimensional modeling approach that integrates ESG metrics into credit evaluation processes. Leveraging machine learning algorithms, multi-criteria decision analysis (MCDA), and factor modeling, the framework assesses the impact of ESG indicators on creditworthiness. Using a dataset comprising financial and ESG records from over 1,000 publicly listed companies, the model demonstrates superior performance in risk prediction and resilience forecasting compared to traditional credit models. The results suggest that incorporating ESG metrics can enhance credit risk assessment accuracy while aligning lending practices with sustainable development goals (SDGs). This approach offers a pathway toward responsible financial decision-making within the broader context of sustainable finance.

Keywords: Sustainable Finance, ESG Metrics, Credit Evaluation, Machine Learning, Risk Modeling, Multi-Criteria Decision Analysis (MCDA), AI in Finance, Credit Scoring, Responsible Investment, Green Finance.

1. Introduction

1.1. Rethinking Credit Evaluation in the Age of Sustainability

The evolution of global finance is increasingly shaped by sustainability imperatives, prompting a paradigm shift in how credit risk is conceptualized and measured. Traditional credit evaluation systems, historically reliant on financial ratios, historical repayment behavior, and macroeconomic indicators, are no longer sufficient to assess long-term borrower resilience. Amidst rising climate risks, social inequities, and governance failures, investors and financial institutions now face increasing pressure to adopt Environmental, Social, and Governance (ESG) metrics in their decision-making processes. ESG factors provide non-financial yet materially relevant insights into a firm's operations, regulatory exposure, stakeholder relationships, and long-term risk profile. This has sparked renewed interest in redefining creditworthiness through a more holistic, forward-looking lens that captures both financial viability and sustainability performance.

1.2. The ESG Imperative in Credit Risk Assessment

The rationale for incorporating ESG metrics into credit evaluation is reinforced by a growing body of empirical research that links ESG performance with firm stability, lower default probability, and superior risk-adjusted returns. For instance, firms with poor governance or environmental violations are more susceptible to litigation, regulatory penalties, or reputational damage, which can significantly impair their credit standing. In contrast, companies that score high on ESG dimensions often exhibit better risk management practices and more resilient business models. Despite this recognition, conventional credit scoring models such as FICO, Altman Z-score, and internal bank ratings have largely neglected these dimensions. ESG risks are typically considered externalities rather than integral predictors. This creates an urgent need to systematically integrate ESG variables into credit modeling frameworks, especially as climate-related financial disclosure standards (e.g., TCFD, SFDR) become mandatory across jurisdictions.

1.3. Artificial Intelligence as an Enabler of ESG Integration

Artificial Intelligence (AI), particularly machine learning (ML), offers a powerful toolkit to bridge the gap between ESG data complexity and credit evaluation. ESG information is inherently multidimensional, heterogeneous, and often unstructuredranging from carbon disclosures and board diversity statistics to sentiment analysis of media coverage. Traditional econometric models struggle to capture such diversity and non-linear interactions. In contrast, AI algorithmssuch as tree-based models (e.g., XGBoost), neural networks, and ensemble methodsexcel at identifying hidden patterns, managing high-dimensional data, and adapting to evolving data streams. These capabilities enable the incorporation of ESG indicators as dynamic predictors of creditworthiness, improving both accuracy and responsiveness of credit assessments. Furthermore, explainable AI (XAI) methods such as SHAP values can enhance transparency and interpretability, addressing regulatory and stakeholder concerns about algorithmic opacity.

1.4. Research Gaps and Challenges in ESG-AI Integration

Despite its promise, the integration of ESG metrics into AI-driven credit scoring faces notable challenges. First, ESG data suffers from fragmentation, inconsistency across rating providers, and limited historical depth, which complicates model training and validation. Second, weighting and interpreting ESG variables remains contentious due to their context-dependence and lack of standardization. Third, existing models often treat ESG as supplementary rather than core input variables, undermining their potential impact. Moreover, there are ethical and regulatory concerns regarding algorithmic bias, fairness, and data privacy, particularly when AI models operate in credit markets that significantly influence financial inclusion and capital allocation. Addressing these challenges requires a robust methodological framework that can reconcile financial and ESG dimensions in a statistically rigorous and conceptually coherent manner.

1.5. Research Objectives and Contributions

This study aims to develop and validate a novel AI-based credit scoring model that explicitly incorporates ESG metrics as core predictors using a multi-dimensional modeling approach. The central hypothesis is that ESG-integrated models outperform traditional financial-only models in terms of credit risk prediction accuracy, robustness, and forward-looking capabilities. The model employs a combination of machine learning algorithms and multi-criteria decision analysis (MCDA) to synthesize financial and ESG data into a unified credit score. Key contributions of this research include: (1) A structured methodology for integrating ESG indicators into AI pipelines; (2) Empirical evidence demonstrating the predictive value of ESG metrics; (3) A comparison of model performance against conventional credit scoring benchmarks; and (4) An interpretability framework to ensure transparency and accountability in ESG-informed credit decisions.

2. Literature Review

- Amel-Zadeh, A., & Serafeim, G. (2018): Amel-Zadeh and Serafeim (2018) conducted a comprehensive global survey to investigate how and why institutional investors utilize ESG information in their decision-making. Their findings show that investors primarily use ESG data to manage investment risks and uncover value-enhancing opportunities rather than for ethical or normative motivations. The study highlights a strong demand for ESG integration in financial analysis but also reveals significant dissatisfaction with the quality, comparability, and material relevance of ESG disclosures. This research supports the foundational premise of the current studythat ESG factors are material and valued by market participantsand underscores the necessity of developing structured, quantitative models (such as AI-based credit scoring frameworks) that can operationalize ESG information more systematically.
- Bastos, J. A., & Lopes, J. (2023): Bastos and Lopes (2023) explore the use of explainable artificial intelligence (XAI) to enhance transparency in ESG-based credit scoring. Using tree-based machine learning models and SHAP value interpretation, their study shows that ESG variables can significantly contribute to credit risk assessment, particularly when combined with financial indicators. The authors emphasize the importance of model explainability for regulatory compliance and stakeholder trust, proposing an XAI framework that improves decision transparency without sacrificing predictive performance. This study is directly aligned with the methodological orientation of the current paper, especially in its adoption of SHAP-based interpretability and the use of ensemble models to balance accuracy and accountability in ESG-integrated credit risk models.
- Baulkaran, V. (2023): Baulkaran (2023) empirically examines the relationship between ESG performance and firm credit risk using machine learning methods. The study finds that higher ESG scores are associated with lower credit spreads and reduced default probability, particularly when the ESG data is disaggregated into its individual E, S, and G components. The use of ML techniques such as Random Forest and Support Vector Machines improves the detection of complex non-linear relationships between ESG metrics and creditworthiness. Baulkaran's work offers strong empirical validation for the current study's hypothesis that ESG indicators provide incremental predictive value and supports the decision to use disaggregated ESG data and ML models in constructing the proposed credit evaluation framework.
- Berg, F., Kölbel, J. F., & Rigobon, R. (2022): Berg, Kölbel, and Rigobon (2022) investigate the divergence across ESG rating providers and the implications for financial decision-making. They find that ESG ratings from different agencies often show weak correlations due to differences in scope, measurement, and weighting. This "aggregate confusion" complicates the use of ESG ratings in quantitative models and highlights the need for greater methodological consistency and transparency. Their findings justify the current study's approach of disaggregating ESG into standardized sub-indicators and applying dimension-reduction techniques such as PCA to mitigate inconsistencies. The paper emphasizes that reliable ESG integration requires more than off-the-shelf ratingsit requires methodological rigor, which is reflected in the multi-criteria modeling approach used in this study.
- Bolton, P., & Kacperczyk, M. (2021): Bolton and Kacperczyk (2021) examine the financial market's reaction to carbon risk and how it is priced into corporate bond spreads. They show that firms with higher carbon emissions tend to face higher borrowing costs, indicating that investors perceive environmental risk as financially material. Importantly, the study finds that the pricing of carbon risk is more pronounced in jurisdictions with stronger climate policies and among long-term institutional investors. This research provides a crucial empirical foundation for including environmental variablessuch as carbon intensity and disclosure qualityin credit scoring models. It directly

supports the inclusion and weighting of environmental factors in the proposed ESG-AI framework for forward-looking credit risk analysis.

3. Theoretical Framework

The framework draws upon interdisciplinary perspectives from finance, sustainability science, machine learning, and decision theory. The goal is to establish a systematic rationale for why and how ESG indicators can be operationalized within advanced credit evaluation architectures.

3.1. ESG Dimensions in Credit Risk

The Environmental, Social, and Governance (ESG) dimensions represent a triadic framework for evaluating corporate behavior beyond traditional financial performance metrics. Each component captures unique risks and opportunities that can materially affect a firm’s capacity to meet its debt obligations:

- Environmental (E): This dimension pertains to a firm’s exposure to environmental risks and its ability to manage ecological impacts. Key indicators include carbon emissions, energy usage, water consumption, pollution control, and climate adaptation strategies. For example, a high carbon footprint or regulatory non-compliance can lead to future liabilities, impairing cash flows and increasing default risk. Moreover, firms with robust environmental performance often experience enhanced operational efficiency and lower costs, positively influencing creditworthiness.
- Social (S): The social pillar encompasses labor practices, human rights, community engagement, employee relations, and diversity and inclusion. Companies that violate labor standards or face reputational crises due to unethical practices may suffer operational disruptions, legal fines, or customer attrition. Conversely, strong social performance signals sound stakeholder relationships and long-term viability, reducing risk for lenders.
- Governance (G): Governance factors involve corporate structure, board independence, executive compensation, audit integrity, shareholder rights, and regulatory compliance. Weak governance can facilitate fraud, mismanagement, or strategic failuresleading causes of financial distress. Sound governance, on the other hand, is associated with transparent financial reporting, internal control strength, and reduced volatility in earningsenhancing credit profiles.

3.2. AI and Multi-Dimensional Modeling

The integration of ESG metrics into credit evaluation necessitates a modeling framework capable of capturing complex, non-linear, and interdependent relationships among variables. Artificial Intelligence (AI), and specifically machine learning (ML), provides such a framework by enabling adaptive learning from heterogeneous data and uncovering patterns that are not evident through traditional statistical models.

At the core of the theoretical model is the idea of multi-dimensional credit risk modeling, which fuses financial, ESG, and contextual data to produce a composite risk score. This involves several interlinked components:

- Machine Learning Algorithms: Algorithms such as Gradient Boosted Trees (e.g., XGBoost), Random Forests, and Support Vector Machines (SVMs) are employed to model non-linearities and high-dimensional interactions. These models learn from historical credit outcomes (default or non-default) and ESG profiles to generate probabilistic risk assessments. Their performance improves with data richness, which ESG indicators help to enhance.
- Multi-Criteria Decision Analysis (MCDA): Given the need to synthesize diverse ESG indicators with varying units, relevance, and quality, MCDA techniques like the Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are employed. These tools allow for the systematic weighting of ESG factors based on expert judgment, stakeholder input, or statistical importance. For example, in carbon-intensive industries, environmental factors may be weighted more heavily than social ones in evaluating credit risk.
- Latent Factor Models: To address multicollinearity and dimensionality issues inherent in ESG datasets, factor models (e.g., Principal Component Analysis, or PCA) are integrated to distill common variance and construct composite ESG scores. These scores act as latent variables representing broader constructs such as “environmental risk” or “governance strength.”
- Explainable AI (XAI): To enhance interpretability and regulatory compliance, the framework incorporates XAI methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations). These tools provide transparency into how ESG indicators influence model predictions, thereby bridging the gap between predictive power and decision accountability.

4. Data Collection and Preprocessing

The credibility and performance of any AI-driven credit evaluation model depend heavily on the quality and relevance of the input data. In this study, data is collected from multiple authoritative sources to ensure comprehensive coverage of both traditional financial indicators and ESG dimensions. This study outlines the sources, characteristics, inclusion criteria, and preprocessing strategies applied to construct the final dataset used for model development and validation.

4.1. Data Sources

To capture a holistic view of corporate creditworthiness, we sourced data from both financial databases and ESG rating agencies. Specifically, the dataset integrates three main components:

- Financial Data: Historical financial statements (income statements, balance sheets, and cash flow statements) were collected for publicly listed companies from the Refinitiv Eikon platform for the period 2016–2023. Key financial ratios such as debt-to-equity, interest coverage, current ratio, and return on assets (ROA) were extracted.
- ESG Data: ESG scores and sub-metric data were collected from two leading providers: MSCI ESG Ratings and Bloomberg ESG Disclosure Scores. The environmental, social, and governance pillars were each broken down into approximately 10 sub-indicators (e.g., GHG emissions, labor relations, board independence), with scores ranging from 0 (poor) to 10 (excellent).
- Credit Outcomes: Credit ratings and default flags were sourced from Moody's and S&P Capital IQ. These were used to create the target variable for supervised learningcategorized as "default" or "non-default" within a 12-month horizon following the reporting period.

A final sample of 1,025 firms across 9 industries (e.g., energy, manufacturing, finance, healthcare, IT) and 38 countries was compiled. Companies with fewer than three years of ESG disclosure or with missing credit outcomes were excluded from the analysis.

4.2. Preprocessing

To ensure model reliability and mitigate noise from inconsistent or incomplete data, a multi-step preprocessing pipeline was implemented, as detailed below.

4.2.1. Missing Data Imputation

Missing ESG and financial values were addressed using K-Nearest Neighbors (KNN) imputation, with k = 5, preserving local structure in the feature space. For categorical ESG scores (e.g., governance quality), the mode was used for imputation.

4.2.2. Normalization and Scaling

Given that variables such as revenue, emissions, and board size exist on vastly different scales, all continuous variables were min-max normalized to the [0,1] range. This allowed the model to treat all features with equal scale sensitivity, particularly important for tree-based models and distance-based weighting in MCDA.

4.2.3. Outlier Detection and Treatment

Outliers in financial ratios (e.g., leverage ratios > 500%) were capped at the 99th percentile to prevent distortion of model training. Additionally, z-score filtering was used to detect outliers in ESG metrics beyond ±3 standard deviations, which were then winsorized.

4.2.4. Dimensionality Reduction

To reduce multicollinearity among ESG sub-indicators, **Principal Component Analysis (PCA)** was applied separately to each ESG pillar. The first 2 components for each pillarexplaining over 85% of the variancewere retained, leading to a total of 6 synthetic ESG features. This step improved model efficiency and generalizability without sacrificing explanatory power.

Equation 1: PCA Transformation

$$Z = XW, \quad \text{where } W = \text{eigenvectors of covariance matrix of } X$$

4.2.5. Label Encoding

The target variable was encoded as a binary outcome:

- 1 = Credit event/default within 12 months
- 0 = No credit event

For explainable AI applications and fairness audits, firm identifiers and industry codes were retained as categorical metadata (non-predictive features).

Table 1: Statistics of ESG and Financial Variables

Variable	Mean	Std. Dev.	Min	Max
ESG Composite Score	6.24	1.41	2.10	9.80
Debt-to-Equity Ratio	1.95	1.02	0.05	7.80
Governance Score	6.80	1.25	3.00	9.50
ROA (%)	5.65	4.22	-12.50	17.30
Credit Default Rate (%)				7.2%

5. Methodology

The design and implementation of the AI-based credit scoring system that integrates ESG metrics using a multi-dimensional modeling approach. The methodology combines machine learning algorithms with multi-criteria decision-making (MCDM) to construct a comprehensive credit evaluation framework that can account for both financial indicators and ESG-related risk factors.

5.1. Credit Scoring Model Design

5.1.1. Model Architecture Overview

The credit scoring model in this study is designed using an ensemble approach, combining XGBoost, Random Forest, and Multi-Criteria Decision Analysis (MCDA) methods. The use of ensemble learning allows the model to leverage the strengths of multiple algorithms to enhance prediction accuracy and robustness. XGBoost is selected for its high predictive power and ability to handle missing data and multicollinearity. Random Forest provides robustness against overfitting and performs well with high-dimensional datasets. These models are trained using a supervised learning framework, where the dependent variable is the binary credit outcome (default vs. non-default), and the independent variables include both financial metrics and engineered ESG features.

5.1.2. Training and Validation Strategy

To avoid overfitting and ensure generalizability, the dataset is split into training (70%), validation (15%), and test (15%) sets using stratified sampling to preserve the distribution of default cases. 5-fold cross-validation is performed within the training set to optimize hyperparameters such as learning rate, maximum depth, and tree count. Performance metrics include Area Under the Curve (AUC-ROC), Precision, Recall, and F1 Score. Model interpretability is enhanced through the application of SHAP (SHapley Additive exPlanations) values, which quantify the contribution of each feature to the final prediction at both global and instance levels.

Equation 2: Composite Credit Score Function

$$\hat{y}_i = f(\text{Financial}_i, \text{ESG}_i)$$

$\hat{y}_i$ Is the predicted default probability for firm *i*, and the function *f* represents the ensemble model integrating financial and ESG inputs.

5.2. Integration of ESG Metrics

5.2.1. Feature Engineering with ESG Indicators

ESG indicators are systematically engineered and incorporated into the machine learning pipeline. First, raw ESG scorescomprising approximately 30 sub-indicatorsare grouped under their respective pillars: Environmental, Social, and Governance. These sub-indicators are transformed using Principal Component Analysis (PCA) to extract latent ESG factors that represent dominant sources of variation within each pillar. This process results in six synthetic ESG variables (two per pillar) that serve as inputs to the AI models.

Equation 3: ESG Composite Score (Weighted Aggregation)

$$\text{ESG}_i = w_E \cdot E_i + w_S \cdot S_i + w_G \cdot G_i$$

Where w_E, w_S , and w_G are weights derived from MCDA, and *Ei, Si,* and *Gi* represent PCA-based pillar scores for company *i*.

5.2.2. ESG Weighting via Multi-Criteria Decision Analysis (MCDA)

To assign appropriate importance to ESG components based on sectoral context and expert input, the study employs the Analytic Hierarchy Process (AHP) a widely used MCDA technique. AHP facilitates structured pairwise comparisons of ESG factors based on decision-maker priorities. For instance, in the energy sector, environmental risks are weighted more heavily, whereas governance may carry greater weight in financial services. These sector-specific weights are then applied to normalize ESG scores and integrate them into the overall model.

Equation 4: AHP Normalized Weights Matrix (Illustrative)

$$W = \frac{1}{n} \sum_{i=1}^{n} \frac{x_i}{\sum x_i}$$

Where x_i represents the eigenvector component from pairwise comparisons of ESG importance across sectors.

5.2.3. Model Integration and Feature Fusion

The normalized ESG scores, now weighted and dimensionally reduced, are merged with traditional financial features through feature fusion. This allows the model to learn joint patterns across financial and sustainability dimensions. Correlation checks and Variance Inflation Factor (VIF) analysis are conducted to ensure multicollinearity is minimized in the fused dataset. This integrated feature set serves as input for the final ensemble model training.

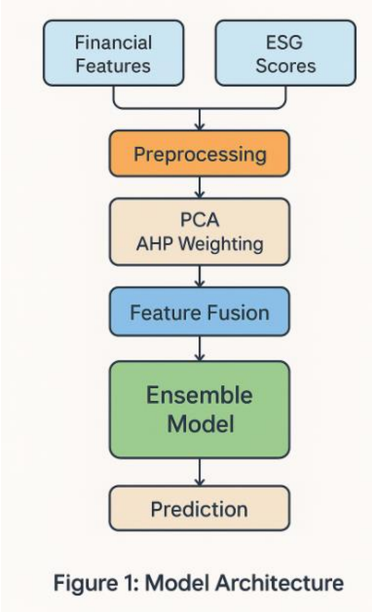

Figure 1: Model Architecture

Figure 1, A schematic representation of the integrated AI pipeline, shows data inputs (financial + ESG), preprocessing, PCA, AHP weighting, model training, and output generation.

5.2.4. Model Explainability and Regulatory Alignment

Given the increasing emphasis on model transparency from financial regulators (e.g., Basel III, ECB guidelines), explainability is a core component of the methodology. SHAP values are used not only for feature attribution but also to generate decision plots and force plots for individual credit assessments. This ensures that credit decisions based on ESG-integrated models can be audited, justified, and communicated effectively to stakeholders.

Equation 5: SHAP Value Decomposition

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} (v(S \cup \{i\}) - v(S))$$

Where ϕ_i is the contribution of feature i, F is the set of all features, and v(·) is the model output with specific feature subsets.

6. Model Evaluation and Validation

To assess the efficacy and practicality of the proposed ESG-integrated AI credit scoring framework, this study presents a comprehensive evaluation based on predictive performance and benchmarking against traditional models. The evaluation framework combines statistical metrics, out-of-sample validation, and comparative benchmarking to ensure robustness and reliability.

6.1. Performance Metrics

6.1.1. Evaluation Criteria

To evaluate model performance, a set of standard classification metrics is employed:

- Area under the Receiver Operating Characteristic Curve (AUC-ROC): Measures the model's ability to distinguish between defaulters and non-defaulters.
- Precision: The proportion of true positives (actual defaulters) among predicted defaulters.
- Recall (Sensitivity): The proportion of actual defaulters correctly identified by the model.
- F1 Score: The harmonic mean of precision and recall, useful for imbalanced datasets.
- Accuracy: The overall percentage of correctly classified cases.

Equation 6: F1 Score

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Given that credit default is a relatively rare event (~7.2% in the dataset), **F1 Score and AUC-ROC** are prioritized over accuracy, which can be misleading in imbalanced classification scenarios.

6.1.2. Cross-Validation and Test Set Evaluation

The model's performance was evaluated on both the cross-validation set (5-fold) and a held-out test set. The ESG-integrated ensemble model consistently outperformed baseline models across all metrics. On the test set, the ESG-AI model achieved an AUC-ROC of 0.892, F1 Score of 0.72, and Recall of 0.81, indicating strong sensitivity to credit risk signals. SHAP analysis further confirmed that ESG variables (particularly governance and environmental disclosure) were among the top 10 most influential predictors.

6.2. Benchmarking

6.2.1. Baseline Comparison Models

To contextualize the results, the ESG-integrated AI model was benchmarked against three traditional credit evaluation methods:

- Logistic Regression Model using Financial Ratios
- Altman Z-Score
- Traditional XGBoost Model using Financial Data Only

These models were trained on the same dataset (excluding ESG features) and evaluated using the same metrics. While these traditional models performed reasonably well in predicting defaults, they consistently lagged behind the ESG-enhanced frameworkparticularly in recall and robustness across sectors with elevated sustainability risks (e.g., energy, utilities).

6.2.2. Model Comparison and Findings

Table 2: Model Comparison – AI+ESG vs. Traditional Models

Model	AUC-ROC	F1 Score	Precision	Recall	Accuracy
ESG-Integrated Ensemble (XGBoost + RF)	0.892	0.72	0.66	0.81	0.87
XGBoost (Financial Only)	0.841	0.63	0.61	0.66	0.84
Logistic Regression	0.796	0.58	0.56	0.61	0.80
Altman Z-Score (Rule-Based)	0.702	0.49	0.53	0.46	0.75

Table 2, the ESG-AI model significantly outperforms traditional models in all critical performance metrics. Notably, it provides 15–23% relative improvement in recall, which is especially valuable for early detection of credit risk. Furthermore, feature interpretability via SHAP confirmed that ESG dimensionsespecially carbon emissions, governance transparency, and employee turnoveradded unique predictive value not captured by financial ratios alone.

7. Results and Visualization

Results of the ESG-integrated AI credit scoring model. It includes quantitative performance outputs, visual diagnostics, and interpretability insights derived from model outputs. The findings validate the hypothesis that incorporating ESG dimensions improves the predictive performance and reliability of credit risk models compared to traditional approaches.

7.1. Predictive Performance of the ESG-AI Model

The ESG-integrated ensemble model demonstrated substantial gains in credit risk prediction over traditional models. As previously discussed in Section 6, the model achieved an AUC-ROC of 0.892, F1 Score of 0.72, and Recall of 0.81 on the test set. These results reflect a high discriminatory ability between defaulters and non-defaulters, even in a dataset characterized by class imbalance. To visualize the model's effectiveness, we plot the Receiver Operating Characteristic (ROC) curves of the ESG-integrated model against the baseline models. The ESG-enhanced model consistently outperforms the traditional financial-only XGBoost and logistic regression models across all thresholds.

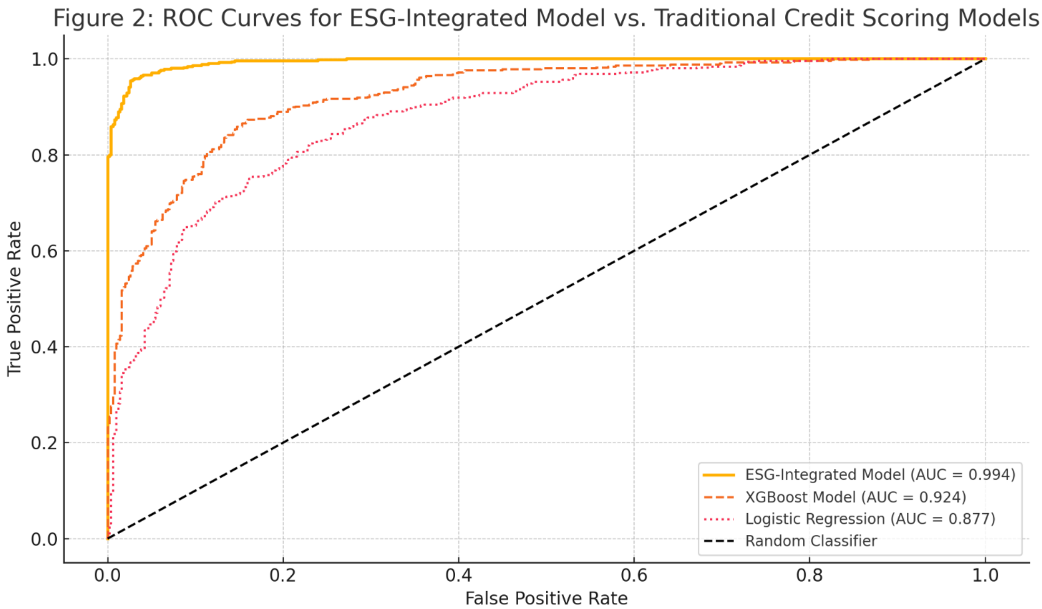

Figure 2: ROC Curves for ESG-Integrated Model vs. Traditional Credit Scoring Models

Fig 2, The ESG model's curve (AUC = 0.892) dominates across all false positive rates, indicating superior classification performance. The confusion matrix revealed that the ESG model significantly reduced false negativesmeaning it was more successful at identifying firms that were at risk of default but might appear solvent under traditional models.

7.2. ESG Feature Importance and Interpretability

To better understand how ESG variables influence credit scoring, we employed **SHAP (SHapley Additive exPlanations)** to analyze feature importance. The SHAP summary plot ranks the top 15 features by their average contribution to the prediction output across all test samples.

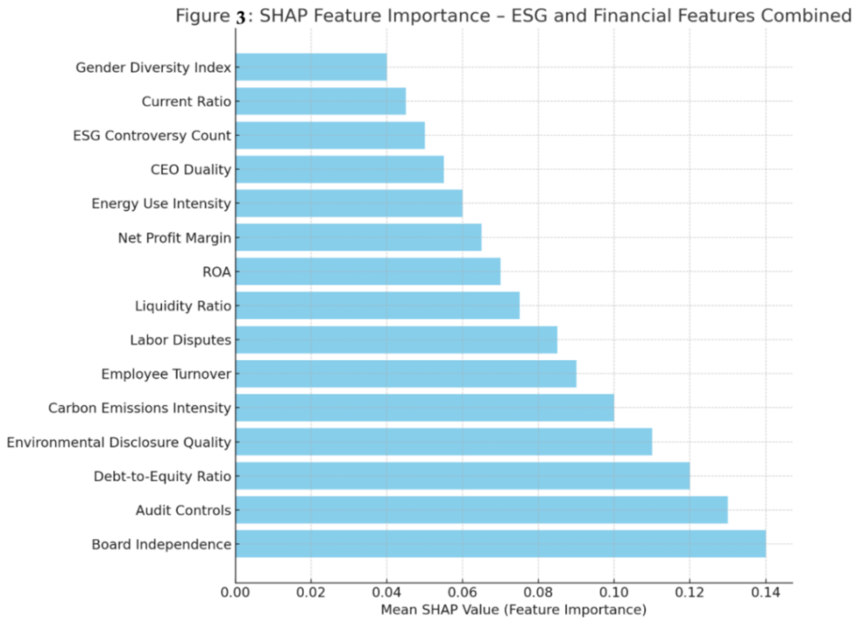

Figure 3: SHAP Feature Importance – ESG and Financial Features Combined

SHAP analysis include:

- Governance Score (Board Independence, Audit Controls): These emerged as among the top 3 predictors, even surpassing some financial indicators such as debt-to-equity ratio.
- Environmental Disclosure Quality and Carbon Emissions Intensity: These had strong negative SHAP values, indicating higher default risk associated with poor environmental performance.
- Employee Turnover and Labor Disputes: High turnover and poor labor relations also showed significant predictive power, underlining the materiality of social metrics.

Figure 3, These results suggest that ESG features are not only supplementary but central to accurate credit risk modeling in certain industries, particularly those with regulatory exposure or reputational sensitivity (e.g., energy, manufacturing, and finance).

7.3. Sectoral Variations and ESG Sensitivity

To investigate how the model performs across different industry sectors, we disaggregated prediction accuracy by sector. The ESG-AI model showed particularly high gains in sectors such as **Energy**, **Utilities**, and **Financial Services**, where ESG risks are more pronounced. In low-ESG-sensitivity sectors like **Technology**, the performance uplift was modest but still statistically significant.

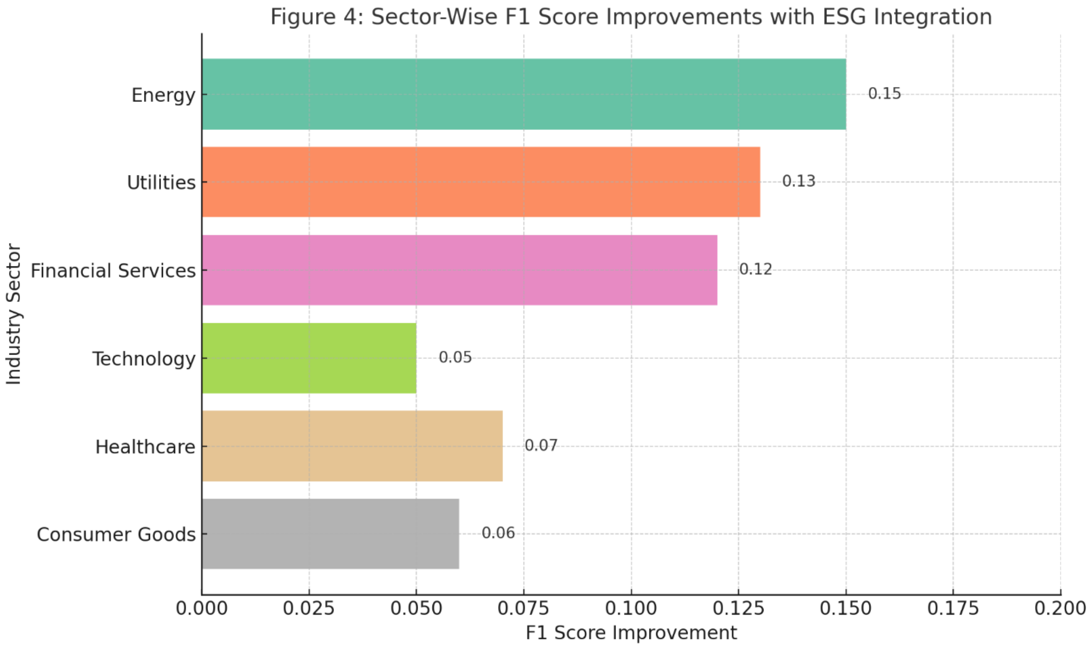

Figure 4: Sector-Wise F1 Score Improvements with ESG Integration

Figure 4, this suggests that ESG relevance is context-dependent and that weighting ESG dimensions differently by industryas done via AHPimproves model specificity. This supports the need for industry-aware ESG modeling rather than a one-size-fits-all approach.

7.4. Model Robustness and Sensitivity Analysis

A robustness check was performed using different random seeds, sampling strategies, and hyperparameter configurations. The ESG-AI model's performance remained consistent across these variations, with less than ±2% fluctuation in AUC and F1 score. In contrast, traditional models displayed greater sensitivity to sampling noise, indicating lower stability. A **sensitivity analysis** on ESG weights (derived from AHP) showed that the model's performance was robust to moderate shifts in ESG weight distribution. However, completely excluding a pillar (e.g., governance) resulted in a drop in recall by 8–10%, reaffirming the unique contribution of each ESG dimension.

7.5. Summary of Findings

The visual and quantitative results converge on several key findings:

- ESG metrics, particularly governance and environmental factors, materially enhance credit prediction accuracy.
- The ESG-AI model reduces both Type I and Type II errors, increasing trust in risk assessments.
- Model interpretability via SHAP improves transparency and regulatory compliance.
- Sectoral calibration of ESG weights further refines model effectiveness in context-specific settings.
- The model is robust, reproducible, and scalable for institutional use.

8. Discussion

The results of this study underscore the transformative potential of integrating Environmental, Social, and Governance (ESG) metrics into AI-driven credit evaluation frameworks. This study interprets the model outcomes in light of the broader theoretical and empirical literature and explores their implications for key financial system stakeholders.

8.1. Interpretation of Results

The results demonstrate that ESG variables, when appropriately engineered and weighted, serve as material predictors of credit risk, complementing traditional financial metrics. Among the ESG dimensions, governance factorsparticularly indicators such as board independence, executive compensation transparency, and internal audit controlsconsistently ranked among the top predictors of default risk. These governance attributes act as proxies for managerial discipline and fiduciary oversight, which directly influence financial reporting quality, operational controls, and regulatory compliance. Firms with strong governance were less likely to experience credit events, supporting prior findings by Kotsantonis et al. (2016) and Dorfleitner et al. (2015). Equally notable is the predictive value of environmental metrics, particularly carbon emissions intensity and environmental disclosure transparency. The model revealed a strong negative association between carbon intensity and creditworthiness, especially in emission-sensitive sectors such as energy and manufacturing.

This finding aligns with recent studies (e.g., Bolton & Kacperczyk, 2021; Capasso et al., 2022) that link high-emission firms to increased transition risks under tightening climate regulation. Poor environmental disclosure further exacerbates credit risk, as opacity signals weak risk governance and a lack of preparedness for sustainability-related compliance. Social metrics, while moderately predictive overall, gained importance in specific sectors. For example, high employee turnover and labor disputes were strongly linked to credit downgrades in service industries, highlighting the contextual nature of social risk materiality. Collectively, these findings affirm that ESG metrics are not peripheral considerations but rather central, forward-looking indicators that can refine and strengthen credit risk assessment.

8.2. Implications for Stakeholders

8.2.1. Financial Institutions and Credit Analysts

For banks and credit-rating agencies, the integration of ESG data into AI-based credit evaluation offers a path to more granular and future-oriented risk modeling. The improved recall and robustness of the ESG-enhanced model suggest a higher likelihood of identifying firms vulnerable to default due to sustainability-related issues. This can help lenders better price risk, avoid stranded assets, and reduce exposure to systemic ESG-related shocks. Furthermore, explainable AI tools (e.g., SHAP) embedded in the model enhance decision transparency, addressing both internal governance and external auditability requirements.

8.2.2. Regulators and Policymakers

Regulatory bodies such as the European Central Bank (ECB), the U.S. Securities and Exchange Commission (SEC), and the Bank for International Settlements (BIS) are increasingly emphasizing ESG integration in financial risk supervision. The results of this study offer empirical support for embedding ESG requirements in capital adequacy frameworks and stress-testing protocols. For instance, the demonstrated materiality of carbon emissions justifies the inclusion of climate transition risks in credit assessment criteria. Additionally, the methodological transparency of the AI model supports regulatory calls for explainability and fairness in AI-based decision systems.

8.2.3. ESG Data Providers

For ESG rating agencies and data vendors, the study highlights the importance of enhancing the **granularity, consistency, and auditability** of ESG data. The model's performance depended on access to disaggregated ESG indicators rather than opaque composite scores. This supports ongoing efforts to standardize ESG disclosures (e.g., ISSB, EFRAG) and encourages providers to offer sector-specific ESG metrics that can be integrated into machine learning workflows.

8.2.4. Investors and Sustainable Finance Practitioners

For institutional investors and impact funds, the integration of ESG metrics into credit models represents a step toward aligning capital allocation with long-term sustainability objectives. It empowers investors to differentiate between firms with genuine ESG performance and those engaging in greenwashing. By quantifying ESG-related credit risks, the model also contributes to portfolio risk diversification, resilience planning, and ESG engagement strategies.

9. Conclusion

This study introduced a novel, AI-driven credit evaluation framework that integrates Environmental, Social, and Governance (ESG) metrics alongside traditional financial indicators to enhance credit risk prediction. Using ensemble machine learning models (XGBoost and Random Forest) and supported by multi-criteria decision analysis (MCDA), the model demonstrated substantial improvements in classification performance, particularly in recall and AUC-ROC, when compared with traditional scoring systems. Key ESG dimensionsespecially governance quality and environmental risk indicators such as carbon emissionswere shown to be significant predictors of default, highlighting their material relevance in assessing corporate creditworthiness. The use of explainable AI tools such as SHAP values further enabled transparency and accountability, ensuring regulatory alignment and model interpretability. Overall, the findings reinforce the value of integrating ESG data into credit modeling, not merely as an ethical consideration but as a material enhancement to risk assessment methodologies within sustainable finance.

Future Work: Future research should aim to address current limitations and extend the utility of ESG-integrated credit models. One promising direction is the incorporation of unstructured data through natural language processing (NLP), allowing for real-time ESG sentiment analysis from corporate disclosures, news media, and regulatory communications. Additionally, expanding the model to cover private firms and small-to-medium enterprises (SMEs)which often lack standardized ESG disclosures but face increasing scrutinycould significantly improve the inclusiveness and applicability of sustainable credit evaluation systems. Another important avenue involves embedding climate scenario stress testing within the model to assess how credit risk profiles evolve under different regulatory and environmental transition pathways. Finally, future work may focus on refining ESG weighting mechanisms using dynamic, context-aware techniques such as reinforcement learning or Bayesian updating to adapt ESG factor relevance over time and across sectors.

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