An Explainable Machine Learning Framework for ESG-Driven Financial Risk Prediction Using Multi-Source Sustainability Indicators

Dr. Divya Chitre[1], Dr. Tejashri Phalle[2], Mrs. Shubhangi Chavan[3]
[1,2,3]*Assistant Professor, School of Information technology, Indira University*

***Abstract*—Financial institutions and investors increasingly recognize that long-term financial stability depends not only on conventional financial indicators but also on environmental, social, and governance (ESG) performance. The growing emphasis on sustainable finance has encouraged organizations to integrate ESG information into financial risk assessment and investment decision-making. However, existing risk prediction models often rely on structured financial variables while overlooking valuable sustainability-related information available from diverse sources such as corporate sustainability reports, ESG rating agencies, regulatory disclosures, news articles, and stakeholder sentiment. Furthermore, many advanced machine learning models provide high predictive accuracy but suffer from limited transparency, making their adoption challenging in highly regulated financial environments where explainability and accountability are essential. This paper proposes an explainable machine learning framework that integrates multi-source sustainability indicators with traditional financial variables to improve financial risk prediction while maintaining model interpretability. The proposed framework combines structured financial data, ESG performance indicators, sustainability disclosures, and external textual information to develop a comprehensive representation of organizational risk. Advanced machine learning algorithms are employed for predictive modeling, whereas Explainable Artificial Intelligence (XAI) techniques, including SHAP (SHapley Additive exPlanations) and Local Interpretable Model-agnostic Explanations (LIME), are incorporated to provide transparent explanations for model predictions. The proposed framework aims to support investors, financial institutions, policymakers, and corporate decision-makers by providing reliable, interpretable, and sustainable financial risk assessments. Unlike conventional approaches that primarily emphasize predictive performance, this research balances prediction accuracy with model transparency and sustainability considerations. The framework also contributes to responsible artificial intelligence by promoting trustworthy decision support systems aligned with sustainable finance objectives. The proposed study establishes a foundation for future empirical validation using publicly available ESG and financial datasets and offers a practical roadmap for integrating explainable machine learning into ESG-based financial risk management.**

***Index Terms*—Explainable Artificial Intelligence, Machine Learning, ESG, Financial Risk Prediction, Sustainable Finance, SHAP, LIME, Sustainability Indicators, Responsible AI, Decision Support Systems.**

I. LITERATURE REVIEW

1.1 Evolution of Financial Risk Prediction

Financial risk prediction has traditionally relied on statistical techniques such as Logistic Regression, Linear Discriminant Analysis, Multiple Discriminant Analysis, and Probit models to predict bankruptcy, credit default, and investment risk. Although these methods are interpretable and computationally efficient, they assume linear relationships and often fail to capture the complexity of modern financial systems. With the rapid growth of structured and unstructured financial data, machine learning has emerged as a more effective alternative. Algorithms such as Random Forest, Support Vector Machine (SVM), XGBoost, LightGBM, and Artificial Neural Networks (ANN) can model complex nonlinear relationships and have demonstrated superior predictive performance. However, most existing models primarily focus on financial indicators while giving limited attention to sustainability-related factors.

1.2 ESG and Sustainable Finance

Environmental, Social, and Governance (ESG) factors have become essential components of sustainable finance, influencing investment decisions, corporate performance, and long-term financial resilience. Strong environmental practices, responsible social initiatives, and effective governance contribute to improved stakeholder trust and organizational sustainability. However, ESG information is often fragmented across multiple sources, and different rating agencies adopt varying assessment methodologies, resulting in inconsistent ESG scores. These challenges highlight the need for frameworks capable of integrating sustainability information from multiple heterogeneous sources.

1.3 Machine Learning in ESG-Based Financial Risk Prediction

Recent studies have demonstrated that incorporating ESG indicators into machine learning models improves the prediction of financial risk, bankruptcy, credit default, and stock market volatility. Ensemble learning algorithms, including Random Forest, XGBoost, CatBoost, and LightGBM, have shown superior performance due to their ability to model nonlinear relationships. In addition, Natural Language Processing (NLP) techniques have enabled the extraction of valuable sustainability insights from corporate reports, news articles, and regulatory disclosures. Despite these advancements, existing studies primarily emphasize predictive accuracy while paying limited attention to model transparency and interpretability.

1.4 Explainable Artificial Intelligence in Financial Decision-Making

The increasing use of machine learning in financial services has raised concerns regarding the interpretability of prediction models. Explainable Artificial Intelligence (XAI) addresses this challenge by providing transparent explanations for model predictions. Techniques such as SHAP and LIME identify the contribution of individual variables, enabling stakeholders to understand and trust prediction outcomes. The integration of XAI into ESG-driven financial risk prediction enhances transparency, supports regulatory compliance, and facilitates responsible AI-based decision-making.

1.5 Multi-Source Sustainability Indicators

Most existing financial risk prediction models rely on single-source ESG ratings, which may not fully capture an organization's sustainability performance. A more comprehensive assessment can be achieved by integrating structured and unstructured information from multiple sources, including ESG ratings, financial statements, sustainability reports, annual reports, regulatory disclosures, corporate governance reports, and financial news. The proposed study leverages this multi-source sustainability intelligence to improve prediction accuracy, model robustness, and decision transparency.

Table 1. Summary of Recent Studies on ESG-Based Financial Risk Prediction

Authors	Year	Methodology	Data Source	Key Findings
Caro-González et al.	2026	Systematic Review (PRISMA), ML, NLP, LLM	64 empirical studies from Scopus	ML models outperform traditional approaches for ESG-driven financial risk prediction. NLP shows promise for analyzing unstructured ESG disclosures.
Lim	2024	Bibliometric Analysis	370 ESG-AI publications	Identified emerging research trends linking AI and ESG in finance.
Kaleem et al.	2024	Random Forest, Gradient Boosting, SVM, Logistic Regression	ESG and financial data from Brazilian companies	ESG variables significantly improve bankruptcy prediction accuracy.
Redondo & Aracil	2024	Systematic Review	Climate-related credit risk literature	Climate risk significantly influences financial risk management.
Ed-Dafali et al.	2025	PRISMA Systematic Review	85 Scopus-indexed articles	Strong governance practices positively influence sustainability and financial performance.
de Souza Barbosa et al.	2023	Systematic Literature Review	Corporate sustainability studies	ESG integration enhances long-term organizational sustainability.
Fiaschi et al.	2020	M-Quantile Regression	ESG controversy dataset	Existing ESG metrics have significant limitations in measuring corporate risk.

II. RESEARCH GAP AND PROBLEM STATEMENT

2.1 Research Gap

Although significant progress has been made in financial risk prediction through machine learning, several important research challenges remain unresolved.

First, most existing prediction models continue to depend primarily on traditional financial indicators such as profitability ratios, liquidity measures, leverage ratios, and stock market performance. While these variables provide valuable financial insights, they fail to capture broader sustainability-related risks that increasingly influence corporate performance.

Second, many studies utilize ESG scores obtained from a single commercial rating agency. Since different agencies adopt different evaluation methodologies, ESG ratings often exhibit considerable inconsistency. This dependence on a single source reduces the reliability and generalizability of predictive models.

Third, the majority of existing machine learning models emphasize prediction accuracy while neglecting model transparency. Financial institutions require interpretable decision-support systems that satisfy regulatory requirements and enable stakeholders to understand why a particular financial risk prediction has been generated.

Fourth, valuable sustainability information available through annual reports, environmental disclosures, regulatory documents, financial news, social media, and corporate governance reports remains significantly underutilized. Existing research rarely integrates these diverse information sources into a unified prediction framework.

Finally, only a limited number of studies investigate the combined application of Explainable Artificial Intelligence (XAI), machine learning, and multi-source ESG information within sustainable financial risk prediction. This gap presents an important opportunity for developing trustworthy AI systems capable of supporting responsible financial decision-making.

2.2 Problem Statement

Despite the growing importance of Environmental, Social, and Governance (ESG) information in sustainable finance, existing financial risk prediction models remain constrained by limited data integration and insufficient model explainability. Most available approaches rely either on traditional financial indicators or single-source ESG ratings, resulting in incomplete representation of organizational sustainability performance. Furthermore, black-box machine learning algorithms provide limited transparency, making it difficult for investors, financial institutions, regulators, and policymakers to understand the rationale behind prediction outcomes.

Therefore, there is a need to develop an explainable machine learning framework capable of integrating multi-source sustainability indicators with conventional financial information while providing transparent, accurate, and trustworthy financial risk predictions. Such a framework would enable more informed investment decisions, improve regulatory compliance, and contribute toward responsible and sustainable financial management.

III. INTRODUCTION

3.1 Background

The global financial landscape is rapidly evolving as sustainability becomes a key determinant of corporate performance and investment decisions. Traditionally, financial risk assessment has relied on quantitative indicators such as profitability, liquidity, leverage, cash flow, and market performance. Although these metrics remain essential, they often fail to capture the broader environmental, social, and governance (ESG) factors that significantly influence an organization's long-term resilience. Recent climate-related events, corporate governance failures, and growing social expectations have demonstrated that financial performance alone is insufficient for assessing organizational risk.

In response to these challenges, ESG principles have emerged as critical components of sustainable finance. Governments, regulators, investors, and financial institutions increasingly encourage organizations to disclose sustainability-related information alongside traditional financial reports. Consequently, companies now generate large volumes of structured and unstructured ESG data through sustainability reports, annual reports, climate disclosures, governance statements, regulatory filings, financial news, and independent ESG rating agencies. While these diverse data sources provide valuable insights into organizational sustainability, differences in reporting standards, disclosure practices, and rating methodologies create significant challenges in integrating and utilizing ESG information for effective financial risk prediction.

Machine Learning (ML) has become a promising approach for financial risk prediction due to its ability to identify complex, nonlinear relationships within large and heterogeneous datasets. Advanced algorithms such as Random Forest, Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN) have demonstrated superior performance in applications such as bankruptcy prediction, credit risk assessment, fraud detection, and stock market forecasting. However, despite their predictive capability, many of these models operate as "black boxes," making it difficult for stakeholders to understand the reasoning behind prediction outcomes. This lack of transparency poses a major challenge in highly regulated financial environments where accountability and explainability are essential.

Explainable Artificial Intelligence (XAI) has emerged as an effective solution to improve the transparency and interpretability of machine learning models. Techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) provide meaningful explanations by identifying the contribution of individual features to model predictions. The integration of XAI into financial risk assessment not only enhances stakeholder confidence but also supports regulatory compliance and trustworthy AI-driven decision-making.

Although previous studies have independently explored financial risk prediction, ESG analytics, and explainable machine learning, limited research has integrated these domains into a unified framework. Most existing models rely on traditional financial variables or single-source ESG ratings, overlooking valuable sustainability information available from multiple structured and unstructured sources. Furthermore, comparatively few studies emphasize both prediction accuracy and model interpretability within the context of sustainable finance.

To address these limitations, this study proposes an Explainable Machine Learning Framework for ESG-Driven Financial Risk Prediction Using Multi-Source Sustainability Indicators. The proposed framework integrates conventional financial variables with sustainability intelligence collected from multiple sources, including ESG ratings, sustainability reports, annual reports, regulatory disclosures, corporate governance reports, and financial news. By combining advanced machine learning algorithms with Explainable Artificial Intelligence techniques such as SHAP and LIME, the framework aims to deliver accurate, transparent, and interpretable financial risk predictions.

The proposed framework is expected to support investors, financial institutions, regulators, and corporate decision-makers by enabling informed, transparent, and sustainable financial decision-making. By integrating multi-source sustainability intelligence with explainable machine learning, this research contributes to the advancement of sustainable finance and the development of trustworthy AI-based decision-support systems for long-term financial risk management.

IV. RESEARCH OBJECTIVES AND RESEARCH QUESTIONS

4.1 Research Objectives

The primary objective of this research is to develop an explainable machine learning framework that integrates multi-source sustainability indicators with conventional financial information to improve the prediction of corporate financial risk while ensuring transparency and interpretability of the prediction process.

The specific objectives of the proposed research are as follows:

- RO1: To identify and integrate multi-source sustainability indicators, including Environmental, Social, and Governance (ESG) metrics, financial statements, sustainability reports, regulatory disclosures, and external textual information, into a unified financial risk prediction framework.
- RO2: To develop a machine learning-based financial risk prediction model capable of capturing complex nonlinear relationships among financial and sustainability variables.
- RO3: To implement Explainable Artificial Intelligence (XAI) techniques, including SHAP

and LIME, to improve the transparency and interpretability of machine learning predictions.
- RO4: To compare the performance of different machine learning algorithms based on predictive accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).
- RO5: To design a trustworthy decision-support framework that assists investors, financial institutions, regulators, and corporate managers in sustainable financial decision-making.

4.2 Research Questions
The proposed study seeks to answer the following research questions:
- RQ1: How can multi-source sustainability indicators improve the prediction of corporate financial risk compared with traditional financial variables?
- RQ2: Which machine learning algorithm provides the best balance between prediction accuracy and computational efficiency for ESG-driven financial risk prediction?
- RQ3: How do Explainable Artificial Intelligence techniques improve the transparency and trustworthiness of financial risk prediction models?
- RQ4: Which Environmental, Social, and Governance indicators have the greatest influence on financial risk prediction?
- RQ5: Can integrating structured financial data with unstructured sustainability information improve the overall performance of financial risk prediction models?

4.3 Expected Outcomes
The proposed research is expected to produce:
- A comprehensive ESG-based financial risk prediction framework.
- Improved prediction accuracy through multi-source sustainability integration.
- Transparent AI models capable of explaining prediction outcomes.
- Better investment decision support.
- Enhanced regulatory compliance through explainable machine learning.
- A scalable framework adaptable across industries and financial markets.

V. RESEARCH HYPOTHESES

The proposed framework is evaluated through the following hypotheses.

Primary Hypothesis
- H1: Integration of multi-source sustainability indicators significantly improves financial risk prediction compared with models using only traditional financial variables.

Secondary Hypotheses
- H2: Ensemble machine learning algorithms achieve higher prediction accuracy than conventional statistical approaches in ESG-driven financial risk prediction.
- H3: Explainable Artificial Intelligence techniques significantly improve the interpretability of financial risk prediction models without reducing predictive performance.
- H4: Environmental indicators contribute significantly toward financial risk prediction.
- H5: Governance indicators have a stronger influence on long-term financial stability than social indicators.
- H6: Combining structured and unstructured sustainability data improves model robustness and prediction reliability.

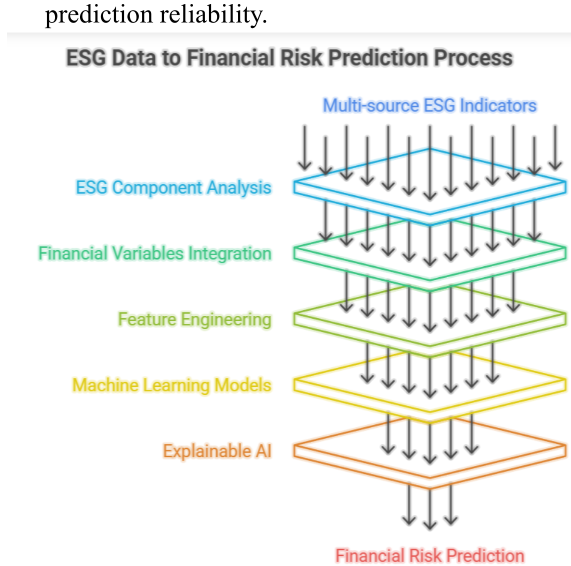


Figure 1: EGS Data to Financial Risk Prediction Process

VI. KEY RESEARCH INNOVATIONS

The proposed study introduces several innovative aspects that distinguish it from existing research in the domain of ESG-based financial risk prediction. By integrating multi-source sustainability intelligence with explainable machine learning, the proposed framework addresses critical limitations of conventional financial risk prediction models and contributes towards the development of transparent, trustworthy, and sustainable decision-support systems. The key research innovations are presented below.

Innovation 1: Multi-Source Sustainability Intelligence Framework

The proposed research introduces a novel framework for integrating sustainability intelligence from multiple heterogeneous data sources into a unified financial risk prediction model. Unlike conventional approaches that primarily rely on financial ratios or single-source ESG ratings, the proposed framework combines structured financial variables with sustainability indicators collected from diverse sources, thereby providing a comprehensive representation of an organization's financial and sustainability performance.

Innovation 2: Explainable ESG-Driven Machine Learning Framework

The study proposes an explainable machine learning architecture that combines advanced predictive models with Explainable Artificial Intelligence (XAI) techniques, including SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations). This integration enhances the transparency, interpretability, and trustworthiness of financial risk prediction by enabling stakeholders to understand the contribution of individual features to the prediction outcomes while maintaining high predictive performance.

Innovation 3: Comprehensive Integration of Structured and Unstructured ESG Information

The proposed framework extends traditional ESG analysis by integrating both structured and unstructured sustainability information. It incorporates data from multiple sources, including:

- ESG Rating Agencies
- Annual Reports
- Sustainability Reports
- Regulatory Filings
- Financial Statements
- News Articles
- Corporate Governance Reports

This comprehensive integration enables the extraction of richer sustainability insights compared to conventional models that depend solely on standardized ESG scores.

Innovation 4: Comparative Evaluation of Explainable Machine Learning Models

The research conducts a systematic comparative evaluation of multiple machine learning algorithms within a common explainability framework. Various predictive models, including ensemble learning techniques and other state-of-the-art machine learning algorithms, are assessed using standardized performance metrics to identify the most effective and interpretable model for ESG-driven financial risk prediction.

Innovation 5: Sustainable Financial Decision-Support Framework

The proposed study develops a practical and explainable decision-support framework designed to assist a wide range of stakeholders in sustainable financial decision-making. The framework aims to support:

- Investors
- Banks and Financial Institutions
- Credit Rating Agencies
- Portfolio Managers
- Regulatory Authorities
- Corporate Decision Makers

By providing transparent financial risk predictions along with interpretable explanations, the framework facilitates informed investment decisions, strengthens regulatory compliance, promotes responsible corporate governance, and advances sustainable finance practices.

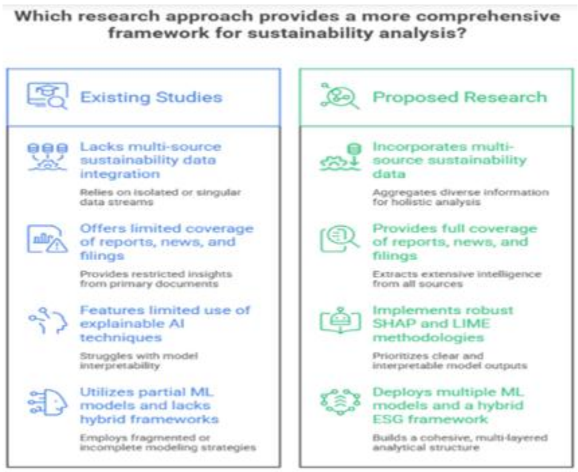


Figure 2. Comparison Between Existing Studies and Proposed Research

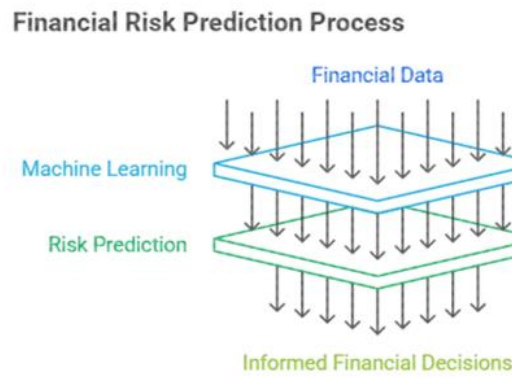


Figure 3. Novel Contribution of the Proposed Framework

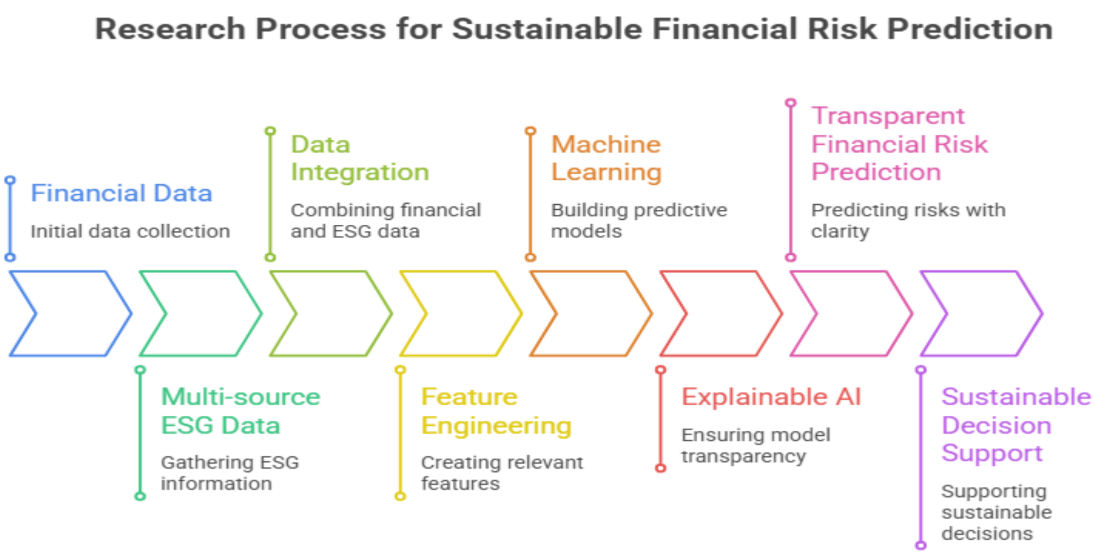


Figure 4. Proposed Research

VII. PROPOSED EXPLAINABLE MACHINE LEARNING FRAMEWORK

7.1 Overview of the Proposed Framework

The increasing adoption of Environmental, Social, and Governance (ESG) principles has transformed the way organizations assess financial risk. Conventional financial risk prediction models primarily rely on structured financial indicators such as profitability, liquidity, leverage, and market performance. Although these indicators provide valuable insights into an organization's financial health, they often fail to capture sustainability-related risks that significantly influence long-term business performance.

To address these limitations, this research proposes an Explainable Machine Learning Framework that integrates conventional financial indicators with multi-source sustainability intelligence for accurate and transparent financial risk prediction. The proposed framework combines structured and unstructured sustainability information from multiple sources and employs explainable artificial intelligence techniques to ensure that prediction outcomes are both reliable and interpretable.

The framework consists of seven sequential stages, beginning with multi-source data acquisition and ending with explainable financial risk prediction. Each stage contributes to improving prediction accuracy while maintaining transparency and supporting sustainable decision-making.

7.2 Architecture of the Proposed Framework
The proposed framework consists of the following components:
Stage 1: Multi-Source Data Acquisition
The first stage involves collecting data from multiple heterogeneous sources to obtain a comprehensive representation of organizational performance. The collected information includes traditional financial indicators, ESG ratings, sustainability reports, annual reports, regulatory disclosures, corporate governance reports, financial news, and publicly available sustainability databases.
The integration of multiple data sources minimizes dependence on a single ESG rating provider and improves the robustness of the prediction model.

Stage 2: Data Preprocessing
The collected datasets undergo preprocessing to improve data quality before model development.
The preprocessing stage includes:

- Missing value treatment
- Duplicate record removal
- Outlier detection
- Data normalization
- Feature encoding
- Text cleaning for unstructured documents
- Data transformation

These preprocessing steps ensure consistency among heterogeneous datasets collected from different sources.

Stage 3: Feature Engineering
Feature engineering transforms raw financial and sustainability information into meaningful predictive variables.
The proposed framework extracts feature from both structured and unstructured data.
Examples include:

Stage 4: Machine Learning Model Development

The engineered features are used to train multiple machine learning algorithms.
The proposed framework compares several supervised learning algorithms including:

- Logistic Regression
- Decision Tree
- Random Forest
- Support Vector Machine
- Gradient Boosting
- XGBoost
- LightGBM
- CatBoost

Each model is evaluated using standardized performance metrics to identify the most suitable algorithm for financial risk prediction.

Stage 5: Explainable Artificial Intelligence
One of the major innovations of this framework is the integration of Explainable Artificial Intelligence (XAI).
The study employs:

- SHAP (SHapley Additive Explanations)
- LIME (Local Interpretable Model-Agnostic Explanations)

These techniques explain

- why a prediction was made,
- which variables influenced the prediction,
- the contribution of each ESG indicator,
- the interaction between financial and sustainability variables.

The explainability layer improves stakeholder confidence and facilitates regulatory compliance.

Stage 6: Model Evaluation

The developed models are evaluated using various performance measures including

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC
- Matthews Correlation Coefficient (MCC)

Cross-validation is also employed to improve model generalization.

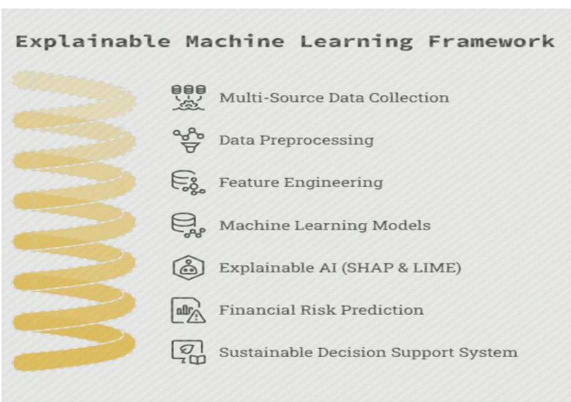
Stage 7: Sustainable Financial Decision Support

The final stage converts prediction outcomes into actionable recommendations.

The explainable framework assists:

- Investors
- Banks
- Credit Rating Agencies
- Regulators
- Corporate Managers
- Portfolio Analysts

in making transparent and sustainable financial decisions.



VIII. RESEARCH METHODOLOGY

8.1 Research Design

This study adopts a quantitative research methodology supported by machine learning and explainable artificial intelligence techniques. The research follows a design science approach aimed at developing, implementing, and evaluating a novel framework for ESG-driven financial risk prediction.

The methodology consists of five major phases: data collection, data preprocessing, feature engineering, predictive model development, and explainability analysis. This structured approach ensures systematic integration of financial and sustainability indicators while enabling transparent prediction outcomes.

8.2 Research Workflow

The overall workflow of the proposed study consists of the following sequential steps:

1. Identification of relevant financial and ESG data sources.
2. Collection of structured and unstructured sustainability data.
3. Data preprocessing and cleaning.
4. Feature extraction and feature engineering.
5. Development of multiple machine learning models.
6. Hyperparameter optimization.
7. Model evaluation using standard performance metrics.
8. Application of SHAP and LIME for model interpretation.
9. Comparative performance analysis.
10. Development of a sustainable decision-support framework.

8.3 Research Process

The proposed methodology follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, adapted to incorporate explainable AI and ESG data integration. The phases include:

- Business Understanding
- Data Understanding
- Data Preparation
- Modeling
- Evaluation
- Deployment (Decision Support)

This structured process ensures reproducibility and facilitates future implementation in financial institutions.

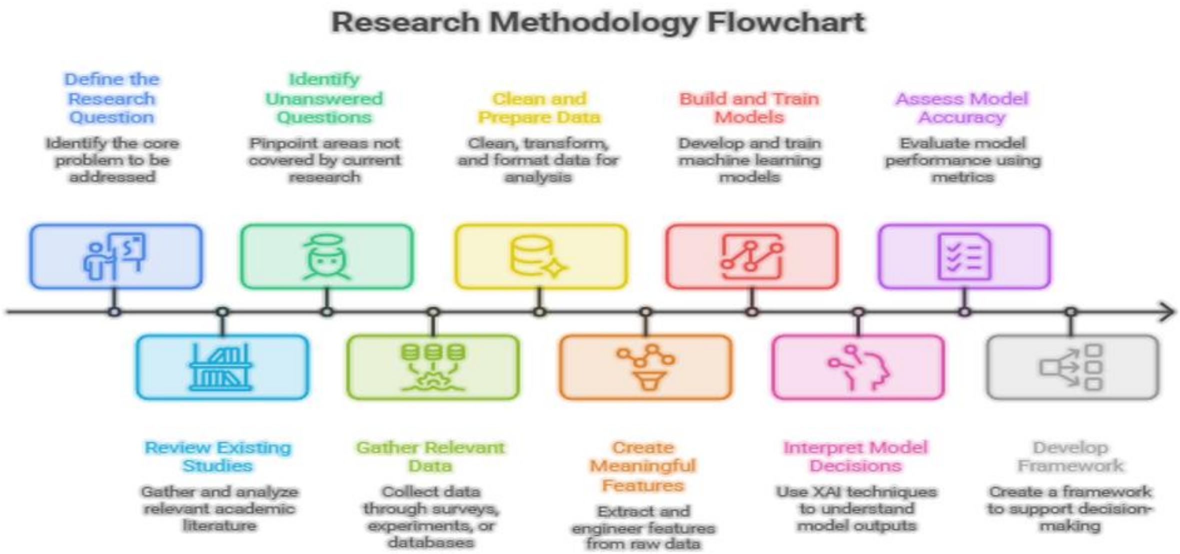


Figure 5. Research Methodology Flowchart

IX. DATA COLLECTION AND MULTI-SOURCE SUSTAINABILITY INDICATORS

9.1 Data Collection Strategy

The proposed framework utilizes a multi-source data collection strategy to capture a comprehensive view of corporate financial and sustainability performance. Data are obtained from both structured and unstructured sources to enhance prediction reliability and reduce dependence on a single information provider. The integration of diverse datasets improves the framework's ability to capture financial, environmental, social, and governance risks.

9.2 Data Sources

The study considers the following categories of data sources:

Table 3: Data Sources

Data Source	Type	Information Collected
Financial Statements	Structured	Profitability, Liquidity, Leverage, Cash Flow
ESG Rating Agencies	Structured	ESG Scores, Environmental Performance, Governance Ratings
Sustainability Reports	Unstructured	Climate Initiatives, CSR Activities, ESG Policies
Annual Reports	Semi-structured	Corporate Performance, Risk Factors
Regulatory Filings	Structured	Compliance Information
Corporate Governance Reports	Semi-structured	Board Structure, Executive Compensation
Financial News	Unstructured	Market Events, ESG News, Corporate Announcements
Stock Market Data	Structured	Share Price, Volatility, Market Capitalization

9.3 Multi-Source Sustainability Indicators

To comprehensively represent organizational sustainability, the framework incorporates indicators across the three ESG dimensions.

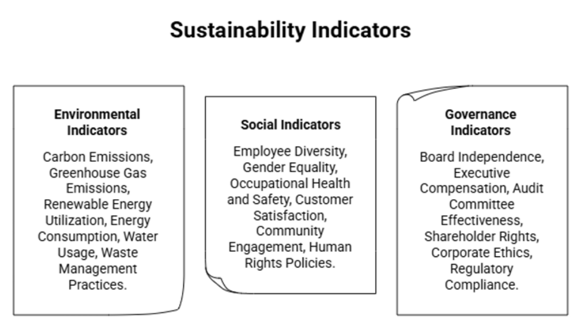


Table 4. ESG Indicators Used in the Proposed Framework

ESG Dimension	Example Indicators	Expected Impact on Financial Risk
Environmental	Carbon emissions, renewable energy use, water consumption	High emissions may increase regulatory and operational risk, while sustainable practices can reduce long-term risk.
Social	Employee diversity, workplace safety, customer satisfaction	Strong social performance can enhance reputation, productivity, and stakeholder trust, thereby lowering financial risk.
Governance	Board independence, executive compensation, audit quality	Effective governance strengthens accountability and reduces the likelihood of financial mismanagement and compliance failures.

Certainly. Below is the conclusion rewritten into three well-structured academic paragraphs, which is the style commonly preferred in Scopus Q1/Q2 journals.

X. CONCLUSION

The increasing emphasis on sustainable finance has highlighted the need for financial risk prediction models that extend beyond traditional financial indicators and incorporate Environmental, Social, and Governance (ESG) considerations. Conventional approaches often rely on financial ratios or single-source ESG ratings, which may not adequately capture the complex and multidimensional factors influencing an organization's long-term financial stability. To address these limitations, this study proposed an Explainable Machine Learning Framework for ESG-Driven Financial Risk Prediction Using Multi-Source Sustainability Indicators. The proposed framework integrates structured financial data with sustainability intelligence collected from diverse sources, including ESG ratings, sustainability reports, annual reports, regulatory disclosures, corporate governance reports, and financial news, thereby providing a more comprehensive and holistic approach to financial risk assessment.

A key strength of the proposed framework lies in its integration of Explainable Artificial Intelligence (XAI) techniques with advanced machine learning algorithms to enhance both predictive performance and model transparency. By incorporating SHAP and LIME, the framework enables stakeholders to understand the contribution of individual financial and sustainability indicators to the prediction outcomes, thereby improving the interpretability and trustworthiness of the model. Furthermore, the comparative evaluation of multiple machine learning algorithms facilitates the identification of the most suitable predictive model for ESG-driven financial risk assessment. The proposed framework has the potential to support investors, financial institutions, regulators, portfolio managers, and corporate decision-makers in making transparent, data-driven, and sustainable financial decisions.

Although the present study proposes a conceptual framework, it establishes a strong foundation for future empirical research in the field of sustainable financial analytics. Future studies can validate the proposed framework using real-world datasets from different industries and geographical regions while exploring advanced techniques such as deep learning, graph neural networks, federated learning, and large language models to further enhance predictive capability and explainability. Overall, the proposed framework contributes to the growing body of research on sustainable finance by providing a transparent, interpretable, and scalable approach to financial risk prediction that aligns with the principles of responsible artificial intelligence and supports long-term sustainable economic development.