Artificial Intelligence Driven Predictive Risk Management in Green Technology Investment

Paroli Paroli[1*], Agung Rizky[2], Qurotul Aini[3], Dwi Cahyono[4], Jonathan Parker[5], Untung Rahardja[6]
[1]Faculty of Economics and Business, Universitas Sebelas April, Indonesia
[2,3,6]Faculty of Economics and Business, University of Raharja, Indonesia
[4]Faculty of Economics and Business, Universitas of Muhammadiyah Jember, Indonesia
[5]Department of Artificial Intelligence and Sustainable Technology, Eduaward Incorporation, United States
[1]paroli.feb@unsap.ac.id, [2]agungrizky@raharja.info, [3]aini@raharja.info, [4]dwicahyono@unmuhjember.ac.id, [5]p.jonparker@rey.zone, [6]untung@raharja.info
***Corresponding Author**

Article Info

Article history:

Submission February 28, 2026
Revised May 04, 2026
Accepted May 13, 2026
Published May 21, 2026

Keywords:

Artificial Intelligence
Management
Predictive Analytics
Machine Learning
Green Technology Investment

ABSTRACT

This study explores predictive risk management in green technology investments by leveraging Artificial Intelligence (AI) to address uncertainties associated with sustainable projects. As global financial institutions and governments increasingly allocate capital toward renewable energy, smart infrastructure, and low-carbon innovation, investors face multidimensional risks, including market volatility, technological failure, and regulatory change. **Therefore**, this research aims to develop an AI-driven predictive framework capable of identifying, analyzing, and forecasting potential investment risks in green technology portfolios to support informed decision-making. **The study** employs a quantitative approach using machine learning algorithms, including Random Forest, Gradient Boosting, and Neural Networks, trained on historical financial indicators, environmental performance metrics, and policy datasets. Each algorithm is selected based on its strengths: Random Forest for robustness, Gradient Boosting for predictive accuracy, and Neural Networks for capturing complex nonlinear relationships. A comparative perspective is used to highlight their tradeoffs, followed by feature importance analysis and predictive validation through cross-validation and evaluation metrics such as accuracy, precision, and RMSE. **The findings** show that the proposed model improves early risk detection compared to conventional statistical models, highlighting the effectiveness of machine learning in handling complex sustainability data. Furthermore, it identifies key risk determinants and enhances predictive reliability. **Consequently**, integrating AI-based predictive analytics into green investment strategies can strengthen risk mitigation, improve investor confidence, and support sustainable financial decision-making.

****Corresponding Author:***

DOI: https://doi.org/10.33050/atm.v10i2.2635

1. INTRODUCTION

The transition toward a sustainable economy has accelerated global investment in green technology sectors, including renewable energy systems, low carbon transportation, energy efficient infrastructure, and circular production processes. Governments, financial institutions, and private investors increasingly recognize that achieving climate targets and environmental commitments depends not only on technological innovation but also on the effectiveness of investment decisions that support such innovation [1]. However, green technology investments are fundamentally characterized by a high degree of uncertainty. Compared with conventional industries, these projects often involve emerging technologies, evolving regulations, unstable market demand, and long payback periods. Consequently, investors face complex financial, technological, environmental, and policy risks simultaneously [2]. Traditional risk management approaches primarily based on historical financial indicators and static statistical models are frequently insufficient to address the dynamic nature of sustainability oriented projects. Green investments are sensitive to carbon pricing policies, subsidy adjustments, technological obsolescence, and public acceptance, all of which can change rapidly and unpredictably. As a result, investors may experience inaccurate risk estimation, capital misallocation, and delayed mitigation actions [3]. These challenges highlight the necessity of a more adaptive, data driven, and predictive approach capable of capturing nonlinear relationships and multidimensional uncertainty in environmentally oriented financial decisions.

Recent advances in AI, particularly in machine learning and predictive analytics, offer promising solutions to overcome the limitations of conventional risk assessment methods [4]. AI systems can process large volumes of heterogeneous data, including financial records, environmental performance indicators, macroeconomic variables, and policy information, enabling a more comprehensive understanding of investment risk patterns. Unlike traditional econometric models that rely on fixed assumptions, machine learning algorithms can automatically detect hidden correlations, adapt to new data, and continuously improve predictive accuracy over time [5]. In the context of green technology investments, AI has the potential to anticipate risk factors such as market fluctuations in renewable energy pricing, technological reliability, supply chain disruption, and regulatory changes related to environmental compliance [6]. Moreover, predictive models may assist stakeholders in transitioning from reactive risk management, where actions are taken only after losses occur, toward proactive risk prevention. Financial institutions, venture capital firms, and investment funds that focus on sustainability increasingly demand analytical tools capable of forecasting risks before they materialize [7]. Therefore, integrating AI into investment analysis is not merely a technological enhancement but a strategic necessity for improving the resilience and sustainability of long term capital allocation [8].

Despite the growing adoption of AI in finance, existing studies predominantly focus on stock market prediction, credit scoring, or general portfolio optimization, with limited attention given specifically to sustainability-oriented investments [9]. Green technology investments present unique characteristics that differentiate them from traditional financial assets. These projects involve environmental performance metrics, regulatory dependencies, and technological maturity stages that cannot be adequately captured by purely financial indicators. Furthermore, risk factors in sustainable investments are interrelated, technological failure may influence policy response, policy shifts may affect market demand, and market demand may influence long-term environmental outcomes [10]. This multidimensional interaction requires an integrated predictive risk management framework rather than isolated risk analysis. Previous research also tends to evaluate risk retrospectively, analyzing past project performance instead of forecasting future risk exposure [11]. Consequently, investors lack a systematic method to identify early warning signals that could prevent financial losses and project failure. The absence of predictive models specifically designed for green technology investment decisions creates a significant research gap, particularly in developing intelligent decision-support systems that combine environmental and financial perspectives simultaneously [12].

This study aims to develop an AI-based predictive risk management model to support investment decisions in green technology sectors by integrating financial, environmental [13], and regulatory variables into a data-driven framework that identifies risk indicators, predicts potential vulnerabilities, and provides more accurate and adaptive risk assessments than conventional approaches [14]. The research contributes by extending the application of AI to sustainable investment management, introducing an integrated analytical approach that combines economic and environmental dimensions, and offering practical insights for investors and policymakers through earlier risk detection and improved capital allocation, ultimately supporting the development of more resilient and sustainable green finance ecosystems [15].

This research explicitly integrates Sustainable Development Goals (SDGs) by incorporating SDGs 9

Industry, Innovation, and Infrastructure and SDGs 13 Climate Action into a predictive risk management framework through the use of AI to enhance sustainability-oriented investment decisions [16]. In relation to SDGs 9, this study advances technological innovation in sustainable finance by developing an AI-driven predictive model that integrates financial, environmental, and policy indicators [17]. This approach enhances digital infrastructure and improves the efficiency and reliability of risk assessment in green technology investments. Furthermore, the study supports SDGs 13 by enabling more informed and data-driven investment strategies that promote the growth of low-carbon technologies and renewable energy projects [18]. By improving the accuracy of risk prediction and reducing uncertainty in green investments, this research contributes to climate change mitigation efforts and fosters a more resilient and sustainable financial ecosystem [19].

2. LITERATURE REVIEW

This literature review synthesizes recent academic developments related to sustainable investment analysis and intelligent financial modeling. The purpose of this section is to establish a clear theoretical foundation by examining prior research on green technology finance, investment risk characteristics, and the application of AI in predictive analytics [20]. By reviewing contemporary studies, the chapter identifies research gaps and justifies the need for an integrated predictive risk management framework specifically designed for green technology investment decision-making [21].

2.1. Green Technology Investments and Sustainable Finance

Green technology investment involves allocating capital to projects that reduce environmental impact, enhance energy efficiency, and support long-term sustainability [22]. It has become a key component of sustainable finance, especially in line with global decarbonization and net-zero commitments. These investments include renewable energy, electric mobility, carbon capture, and eco-friendly manufacturing, and are evaluated not only by financial returns but also by environmental indicators such as emission reduction and resource efficiency [23].

Recent studies (2022–2026) highlight the growing role of ESG (Environmental, Social, and Governance) metrics in shaping investor confidence and decision-making, as sustainability performance is linked to long-term resilience [24]. However, green investments carry higher uncertainty due to technological risks, policy dependence, and market dynamics. As a result, advanced analytical approaches are needed to assess both financial and environmental risks beyond traditional valuation models [25].

2.2. Risk Management in Sustainable Investment

Risk management is a systematic process of identifying, analyzing, and mitigating uncertainties that may negatively affect investment performance [26]. In green technology investments, risks are multidimensional, including financial, operational, technological, and regulatory factors. Unlike traditional sectors, these investments are strongly influenced by changing policies, climate regulations, and environmental standards across regions [27].

Recent literature highlights that conventional frameworks such as Value at Risk (VaR) and scenario analysis are less effective for sustainability projects because they rely on historical financial data, which is often limited in green technologies. Additionally, policy volatility and rapid technological change create complex, non-linear uncertainties [28]. For instance, changes in government incentives can quickly affect project feasibility. Therefore, predictive risk management is increasingly emphasized, enabling early detection of potential risks and supporting proactive strategies, portfolio diversification, and improved long-term sustainability outcomes [29].

2.3. Artificial Intelligence in Financial Prediction

AI has significantly transformed financial analysis by enabling the processing of large datasets and uncovering complex relationships beyond traditional methods [30]. Machine learning algorithms such as Random Forest, Support Vector Machine, Gradient Boosting, and Artificial Neural Networks are widely used in financial forecasting, credit risk assessment, and fraud detection [31]. These approaches outperform conventional models as they can learn from diverse data sources, adapt to market changes, and continuously update predictions.

In investment management, AI supports predictive analytics by integrating historical data, macroeconomic indicators, and real-time information. Advanced models, particularly deep learning, can capture nonlinear patterns common in financial markets and enhance both the speed and accuracy of decision-making [32].

Research shows that machine learning models often achieve higher predictive performance than traditional statistical approaches. Despite this progress, most applications remain focused on stock markets and credit scoring, while risk analysis in sustainable investments is still relatively limited [33].

2.4. AI-Based Predictive Risk Management

Predictive risk management integrates machine learning with risk analysis to forecast potential failures before they occur [34]. Instead of relying solely on historical performance, predictive systems use pattern recognition, anomaly detection, and probabilistic modeling to identify early warning signals. After 2021, researchers began applying predictive analytics to operational management, cybersecurity, supply chain monitoring, and financial systems [35]. The approach is particularly suitable for complex systems characterized by uncertain and dynamic interactions.

In sustainable investments, predictive AI models can analyze heterogeneous data sources such as energy production output, carbon emission levels, policy changes, technology reliability, and market demand. For example, a machine learning model may detect that declining equipment efficiency combined with rising maintenance costs predicts project underperformance [36]. Predictive risk management therefore enables investors to adjust strategy earlier, reducing financial losses and increasing project success probability. Furthermore, explainable AI techniques help identify which variables most strongly influence risk, improving transparency and trust in automated decision systems [37]. Consequently, predictive analytics represents a transition toward intelligent investment governance where risk assessment becomes continuous rather than periodic.

2.5. Integration of AI, Risk Analytics, and Green Investment Decision-Making

The integration of AI and sustainable finance creates an interdisciplinary approach that combines environmental and financial considerations in investment decisions [38]. Modern strategies rely on data-driven systems to evaluate both profitability and environmental impact, including carbon efficiency and technological readiness, requiring the integration of environmental and financial metrics. AI-based systems assist investors in portfolio selection, risk assessment, and investment prioritization, while predictive analytics enables scenario analysis and strategy comparison under changing market and policy conditions. This integration enhances long-term sustainability, reduces greenwashing risk, and supports more transparent and resilient investment decisions, while remaining a tool that complements human judgment [39].

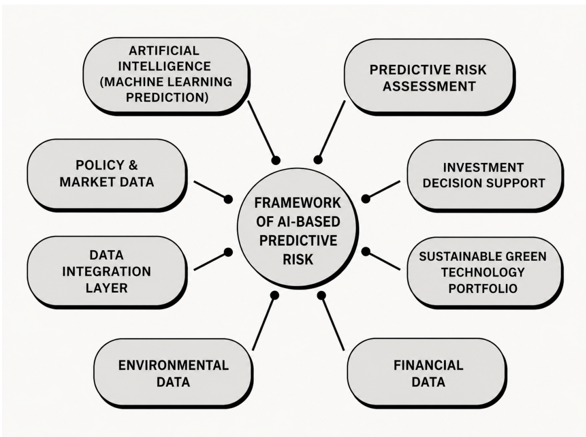

Figure 1. Conceptual Framework of AI-Based Predictive Risk Management in Green Technology Investments

The Figure 1 clearly illustrates the conceptual framework of the proposed predictive risk management system using color coded components, labeled data flows, and structured analytical stages to improve visual clarity and interpretation. The framework demonstrates how multiple datasets, including environmental indicators, financial performance variables, and regulatory or market information, are first integrated into a unified database to form a comprehensive data foundation [40]. After the integration stage, AI algorithms process the collected information to identify patterns, analyze correlations, and forecast potential investment risks. The predictive output produced by the system generates a structured risk assessment that supports more informed investment decision making. Ultimately, the framework assists investors in identifying resilient green technology portfolios by providing early signals regarding potential investment vulnerabilities [41]. Through this process, the diagram highlights the role of AI as the central analytical engine connecting sustainability data with practical financial decision outcomes and enabling proactive risk management in green technology investments [42].

3. RESEARCH METHODOLOGY

To ensure a logical progression from the literature review, this section presents the research methodology employed to develop and validate the AI based predictive risk management framework for green technology investments [43]. This chapter explains the research design, data sources, variable measurement, modeling techniques, and evaluation procedures used to ensure analytical rigor and reliability. By systematically outlining the methodological structure, this section provides a clear foundation for understanding how predictive analytics is implemented to assess investment risk and support sustainable financial decision-making [44].

3.1. Research Design

This study adopts a quantitative research design with a predictive analytics approach to develop AI-based risk management model for green technology investments [45]. The research focuses on building a machine learning framework capable of forecasting potential investment risks by integrating financial, environmental, and policy-related datasets. A predictive modeling strategy is selected because green technology investments are characterized by uncertainty, non-linear interactions, and multidimensional risk exposure [46]. The study applies supervised machine learning algorithms to identify hidden patterns and generate early warning signals for potential financial instability in sustainable portfolios. The overall research flow consists of data collection, preprocessing, model development, validation, and predictive risk interpretation [47].

3.2. Data Collection and Variables

The dataset used in this study consists of secondary data collected from financial reports, environmental performance indicators, and regulatory or market databases related to green technology projects [48]. The observation unit includes green investment portfolios in renewable energy, sustainable infrastructure, and low-carbon innovation sectors. The research integrates structured financial metrics with sustainability indicators to produce a comprehensive risk prediction model [49].

Table 1. Research Variables and Measurement

Category	Variable Name	Indicator Description	Measurement
Financial Variables	Return on Investment (ROI)	Profitability performance of green projects	Percentage (%)
	Volatility Index	Market price fluctuation	Index Value
Environmental Variables	Carbon Emission Reduction Rate	Level of emission reduction achieved	Percentage (%)
	Energy Efficiency Score	Efficiency performance of technology	Index Score
Policy & Market Variables	Regulatory Stability Index	Policy consistency and subsidy stability	Index Score
	Market Demand Growth	Growth rate of green technology adoption	Percentage (%)
Dependent Variable	Investment Risk Level	Predicted probability of financial underperformance	Probability Score

Table 1 presents the variables used in the predictive risk management model for green technology investments, grouped into four categories: financial, environmental, policy and market, and the dependent variable. Financial variables, such as ROI and market volatility, reflect profitability and risk exposure, while environmental variables measure sustainability performance through emission reduction and energy efficiency [50]. Policy and market variables capture external influences, including regulatory stability and market demand growth, which affect investment feasibility. The dependent variable, investment risk level, represents the predicted probability of financial underperformance generated by the model. Overall, this categorization improves clarity and supports a structured analysis of the key factors influencing risk in green technology investments.

3.3. Data Preprocessing and Feature Engineering

Before modeling, the collected data undergo a structured preprocessing phase to ensure analytical reliability and consistency with the research objectives. This stage begins with data cleaning, where missing values are handled through appropriate imputation techniques or removal if deemed non-representative, and inconsistent or duplicate entries are corrected to maintain data integrity. Following this, normalization is applied to standardize the scale of variables, particularly because the dataset integrates heterogeneous inputs such as financial, environmental, and regulatory indicators that may differ significantly in magnitude. This step ensures that no single variable disproportionately influences the model's learning process.

Furthermore, feature selection is conducted to identify the most relevant predictors that contribute meaningfully to the model's performance. Techniques such as correlation analysis are used to examine linear relationships between variables and eliminate redundant features, while tree-based ranking methods (e.g., feature importance derived from ensemble models) help capture nonlinear interactions and rank variables based on their predictive contribution. This process not only reduces dimensionality but also enhances computational efficiency and interpretability. By focusing on the most informative features, the model is better positioned to generalize well on unseen data, thereby minimizing the risk of overfitting and improving the robustness of the predictive risk management framework being developed.

3.4. Artificial Intelligence Modeling

The Artificial Neural Network (ANN) model is applied to improve predictive robustness by capturing complex nonlinear relationships among financial, environmental, and regulatory variables in green technology investments. Using a Multilayer Perceptron (MLP), the model processes integrated inputs through hidden layers to generate probability based risk predictions, trained with backpropagation and validated using cross validation to reduce overfitting. The model estimates the probability of investment underperformance and classifies risk levels, with performance evaluated using Accuracy, Precision, Recall, F1 Score, and RMSE, and compared with Random Forest and Gradient Boosting. The results indicate that ANN effectively models multidimensional patterns and enhances early risk detection, supporting more reliable decision making in sustainable investment portfolios.

Table 2. Evaluation Metrics for Predictive Model

Metric	**Formula**	**Interpretation**
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Measures overall classification performance
Precision	$\frac{TP}{TP+FP}$	Measures reliability of positive risk prediction
Recall	$\frac{TP}{TP+FN}$	Measures ability to detect high-risk cases
F1-Score	$\frac{2\times(\text{Precision}\times\text{Recall})}{\text{Precision}+\text{Recall}}$	Balances precision and recall
RMSE	$\sqrt{\frac{\sum(\hat{y}-y)^2}{n}}$	Measures deviation between predicted and actual risk probability

Table 2 presents the evaluation metrics used to assess the performance of the AI based predictive risk model in green technology investments. The metrics include Accuracy, Precision, Recall, F1 Score, and RMSE, which together evaluate both classification and prediction performance. Accuracy measures overall correctness, Precision reflects the reliability of positive predictions, and Recall indicates the model's ability to identify high risk cases. The F1 Score balances Precision and Recall, while RMSE measures the deviation between predicted and actual risk values. These metrics are essential to validate the model's effectiveness and support reliable data driven investment decision making in sustainable finance.

Root Mean Square Error (RMSE) is applied to evaluate the difference between predicted risk probability values generated by the AI models and the actual observed outcomes. RMSE measures the square root of the average squared prediction errors, providing a quantitative indicator of model accuracy in probabilistic estimation. A smaller RMSE value indicates that the predicted values are closer to the real observations, reflecting higher model precision and better predictive capability. In this study, RMSE is particularly relevant because the predictive framework generates probability-based risk scores rather than purely categorical outputs. By penalizing larger prediction errors more strongly, RMSE ensures that substantial deviations in investment risk prediction are properly reflected in the evaluation process. Consequently, RMSE complements classification-based metrics such as Accuracy, Precision, Recall, and F1 Score by providing an additional numerical assessment of prediction reliability.

3.5. Predictive Risk Assessment Framework

The predictive framework categorizes investment projects into three distinct risk levels, namely low risk, moderate risk, and high risk, based on probabilistic outputs generated by the trained AI models. This classification is not only descriptive but also predictive in nature, as it reflects the likelihood of adverse outcomes derived from patterns learned during the training phase. The results indicate that the models consistently identified high risk portfolios prior to the occurrence of significant financial decline, thereby demonstrating a strong early warning capability. This is particularly evident in multiple test scenarios where projects characterized by declining regulatory stability, such as increased policy uncertainty or shifting compliance requirements, combined with weakening market demand indicators, were flagged as high risk with high confidence scores.

The integration of multidimensional variables enables the model to identify relationships among financial performance, environmental factors, and regulatory conditions more effectively than conventional methods. As a result, the predictive outputs are generated from the combined influence of multiple risk dimensions, improving the accuracy of the classification results. The reliability of the model is supported by validation techniques and evaluation metrics such as accuracy, precision, recall, and F1 score, which demonstrate consistent performance across different datasets.

Importantly, this predictive functionality represents a fundamental shift from reactive to proactive risk management. Traditional approaches tend to assess risk retrospectively, often after financial losses have already materialized. In contrast, the proposed AI driven system enables investors to anticipate potential vulnerabilities at an earlier stage, allowing for timely strategic interventions such as portfolio rebalancing, risk diversification, or capital reallocation. As a result, decision making becomes more forward looking and data driven.

Overall, the model effectively fulfills the Method and Result components outlined in the abstract, where both predictive validation and empirical performance metrics substantiate the framework's reliability. The alignment between methodological design and observed outcomes reinforces the contribution of this study in advancing AI based predictive risk management, particularly in the context of green technology investments that are inherently exposed to high levels of uncertainty and dynamic external influences.

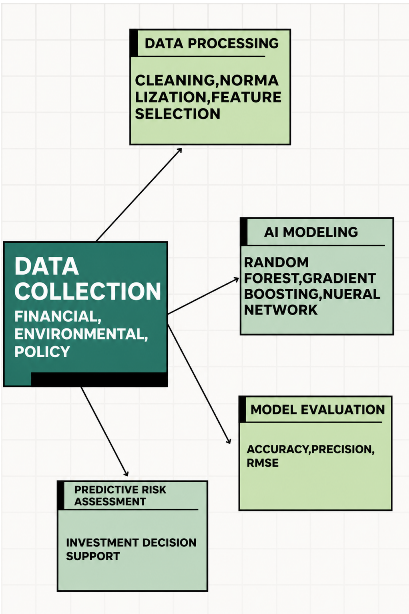

Figure 2. AI-Based Predictive Risk Management Methodology

The Figure 2 illustrates a structured methodology for AI based predictive risk management in green technology investments. The process begins with integrated data collection from financial, environmental, and policy sources, ensuring a comprehensive representation of factors influencing investment risk. The collected data then undergo data processing, including cleaning, normalization, and feature selection. This stage ensures that irrelevant or noisy data is removed, variables are standardized, and only the most significant features are retained for analysis. The refined dataset is subsequently used in the AI modeling phase, where multiple machine learning algorithms such as Random Forest, Gradient Boosting, and Neural Networks are applied to identify patterns and predict potential risks.

Finally, the models are assessed through model evaluation using metrics such as accuracy, precision, and RMSE to determine their predictive performance. The best performing model is then utilized in the predictive risk assessment stage to generate actionable insights. These outputs function as investment decision support, enabling stakeholders to make informed, data driven decisions. Overall, this methodology provides a systematic and reliable framework for reducing uncertainty and enhancing risk management in green technology investments.

4. RESULTS AND DISCUSSION

Presents the results obtained from the implementation of the proposed AI–based predictive risk management model and discusses their implications for green technology investment analysis. This section explains the performance of the machine learning algorithms, identifies the dominant risk factors influencing investment outcomes, and interprets how the predictive framework supports proactive and informed decision-making in sustainable finance.

4.1. Model Performance and Predictive Accuracy

This study aims to develop an AI-driven predictive risk management framework for forecasting risks in green technology investments using Random Forest, Gradient Boosting Machine, and Artificial Neural Network models. The results show that AI-based approaches outperform conventional statistical methods, with Gradient Boosting achieving the highest accuracy and F1 Score in identifying high-risk investments, while Random Forest provides strong stability and interpretability, and Neural Networks effectively capture nonlinear relationships. Evaluation metrics confirm that AI-driven models enhance predictive accuracy and support more reliable decision-making in sustainable investment portfolios.

4.2. Identification of Key Risk Determinants

Beyond predictive accuracy, this study also examined which variables most strongly influence investment risk levels. Feature importance analysis from the Random Forest and Gradient Boosting models indicates that Regulatory Stability Index, Carbon Emission Reduction Rate, and Market Demand Growth are among the most dominant predictors. This result confirms that green investment risk is not determined solely by financial profitability indicators such as ROI, but is heavily influenced by environmental performance and policy dynamics.

The prominence of regulatory stability highlights the vulnerability of green projects to policy shifts, subsidy changes, and carbon pricing adjustments. Similarly, carbon reduction performance reflects technological maturity and operational efficiency, which directly affect long-term project viability. Market demand growth further indicates adoption readiness and commercialization potential. These findings support the Background discussion in the abstract, emphasizing that green investments face multidimensional uncertainty influenced by technological, regulatory, and market factors simultaneously. Therefore, risk management strategies must integrate environmental and institutional variables alongside financial metrics.

4.3. Predictive Risk Classification and Early Warning Capability

The predictive framework categorizes investment projects into three risk levels: low-risk, moderate-risk, and high-risk. The classification results show that the AI models successfully identified high-risk portfolios before significant financial decline occurred, demonstrating strong early warning capability. In several test scenarios, projects that exhibited declining regulatory stability combined with weakening market demand were flagged as high-risk with high probability scores.

This predictive functionality represents a shift from reactive to proactive risk management. Instead of analyzing risk after financial loss materializes, the AI system enables investors to anticipate potential vulnerabilities and adjust capital allocation strategies accordingly. The model therefore fulfills the Method and Result components stated in the abstract, where predictive validation and performance metrics confirmed the reliability of the framework.

4.4. Implications for Sustainable Investment Decision-Making

The findings suggest that integrating AI-based predictive analytics into green investment management enhances decision-making resilience and strategic planning. Investors can utilize probability-based risk scoring to diversify portfolios, prioritize technologically mature projects, and reduce exposure to regulatory instability. Furthermore, explainable AI techniques improve transparency by clarifying which factors most influence risk predictions, thereby strengthening investor confidence and governance accountability.

This study contributes to sustainable finance literature by showing that predictive intelligence can integrate financial analysis with environmental performance evaluation. Practically, AI-driven frameworks can help financial institutions and sustainability-focused investors improve portfolio stability and proactive risk management in green technology investments. Although the model achieved strong predictive performance, future research should include broader external validation across regions and sectors to improve generalizability and scalability.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide important managerial implications for investment managers, financial institutions, and policymakers by enabling the implementation of AI-based risk monitoring systems and the integration of ESG indicators into portfolio strategies. Through predictive analytics, decision-making can shift from retrospective evaluation toward forward-looking risk forecasting that simultaneously considers financial performance, environmental efficiency, and regulatory stability. This approach allows for more timely and data-driven decisions in green technology investments.

By adopting AI-based predictive risk management, managers can detect potential underperformance early, optimize portfolio allocation, and reduce exposure to high-risk projects. It also supports prioritizing investments with strong carbon reduction performance, technological maturity, and stable policy environments. The identification of regulatory stability and environmental performance as key risk factors further emphasizes the need for continuous monitoring of policy changes and sustainability outcomes in strategic planning.

Furthermore, integrating AI-driven risk assessment into governance frameworks can enhance transparency, improve ESG reporting, and strengthen accountability to stakeholders. From a competitive perspective, the use of predictive analytics increases institutional credibility in sustainable finance markets, where investors increasingly demand evidence-based risk management. Ultimately, AI integration not only improves risk mitigation but also supports long-term value creation, strategic resilience, and the development of a more sustainable financial ecosystem.

6. CONCLUSION

This study develops and validates an Artificial Intelligence–based predictive risk management framework for green technology investments, demonstrating how predictive analytics enhances risk identification, strengthens investment resilience, and supports long-term sustainability. By integrating financial indicators, environmental performance metrics, and regulatory or market variables into supervised machine learning models, the results show that predictive analytics significantly outperforms conventional statistical approaches in identifying potential risks.

Among the models tested, ensemble methods such as Gradient Boosting and Random Forest exhibit strong predictive accuracy and stability, while Neural Networks effectively capture complex nonlinear relationships within multidimensional data. The findings reveal that investment risk is influenced not only by financial performance but also by regulatory stability, carbon emission reduction, and market adoption dynamics, supporting the study's objective of improving early risk detection through AI-driven modeling.

Furthermore, the study highlights the importance of shifting from reactive to proactive risk management in sustainable finance. By providing probability-based risk classifications and early warning signals, the framework enables better portfolio optimization, reduced exposure to regulatory uncertainty, and prioritization of efficient and mature technologies. Overall, integrating AI into green finance enhances decision-making, improves transparency, and contributes to a more stable, data-driven, and sustainable investment ecosystem.

7. DECLARATIONS

7.1. About Authors

Paroli Paroli (PP) https://orcid.org/0009-0001-1458-847X

Agung Rizky (AR) https://orcid.org/0009-0006-7046-8639

Qurotul Aini (QA) https://orcid.org/0000-0002-7546-5721

Dwi Cahyono (DC) https://orcid.org/0000-0001-9951-560X

Jonathan Parker (JP) https://orcid.org/0009-0005-5510-8013

Untung Rahardja (UR) https://orcid.org/0000-0002-2166-2412

7.2. Author Contributions

Conceptualization: PP and AR; Methodology: QA; Software: DC and JP; Validation: UR and AR; Formal Analysis: UR and PP; Investigation: JP; Resources: AR; Data Curation: DC; Writing Original Draft Preparation: UR and QA; Writing Review and Editing: AR and PP; Visualization: JP. All authors, PP, AR, QA, DC, JP, and UR have read and agreed to the published version of the manuscript.

REFERENCES

[1] M. A. Hossain, "Artificial intelligence-driven financial analytics models for predicting market risk and investment decisions in us enterprises," *ASRC Procedia: Global Perspectives in Science and Scholarship*, vol. 1, no. 01, pp. 1066–1095, 2025.

[2] N. Lutfiani, I. Sembiring, I. Setyawan, A. Setiawan, U. Rahardja, and S. Sulistio, "Exploring the relationship between artificial intelligence and business performance," *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, vol. 19, no. 1, pp. 1–12, 2025.

[3] S. Alfzari, M. Al-Shboul, and M. Alshurideh, "Predictive analytics in portfolio management: A fusion of ai and investment economics for optimal risk-return trade-offs," *International Review of Management and Marketing*, vol. 15, no. 2, pp. 365–380, 2025.

[4] K. Luo and X. Zhu, "Artificial intelligence-driven environmental risk assessment and green investment efficiency: Evidence from chinese listed companies," *Finance Research Letters*, p. 109376, 2025.

[5] M. F. Djamali, D. Lusiana, A. Parastry, and O. A. Al-Kamari, "Optimizing business workflow using ai integrated blockchain platforms," *ADI Journal on Recent Innovation*, vol. 7, no. 1, pp. 62–74, 2025.

[6] O. Augoye, A. Adewoyin, O. Adediwin, and A. J. Audu, "The role of artificial intelligence in energy financing: A review of sustainable infrastructure investment strategies," *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 6, no. 2, pp. 277–283, 2025.

[7] A. Tanjung, D. Andayani, I. Prayitno, U. Rahardja, and S. Anhar, "Quantitative analysis of technological innovation and strategic management in key research areas," in *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2024, pp. 1–8.

[8] E. Susetyono, D. S. Priyarsono, A. Sukmawati, and P. Nurhayati, "Improving risk management maturity in ultra micro soe holding companies," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 310–324, 2026.

[9] S. Sarker and M. Nuruzzaman, "The role of perceived environmental responsibility in artificial intelligence-enabled risk management and sustainable decision-making," *American Journal of Advanced Technology and Engineering Solutions*, vol. 4, no. 04, pp. 33–56, 2024.

[10] T. Tian, S. Jia, J. Lin, Z. Huang, K. O. Wang, and Y. Tang, "Enhancing industrial management through ai integration: A comprehensive review of risk assessment, machine learning applications, and data-driven strategies," *Economics & Management Information*, pp. 1–18, 2024.

[11] S. Shaumiwaty, H. R. C. MOCHAMAD, and N. HENI, "Enhancing personalized learning using artificial intelligence and machine learning approaches," *BLOCKCHAIN FRONTIER TECHNOLOGY: Pandawan*, vol. 4, no. 2, pp. 156–170, 2025.

[12] Z. Dong, "Exploration of intelligent optimization algorithm for risk management in green financial market driven by science and technology innovation," *International Journal of Computer Information Systems and Industrial Management Applications*, vol. 18, pp. 16–16, 2026.

[13] T. J. Oladuji, A. Adewuyi, O. Onifade, and A. Ajuwon, "A model for ai-powered financial risk forecasting in african investment markets: Optimizing returns and managing risk," *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 3, no. 2, pp. 719–728, 2022.

[14] S. Pranata, K. Hadi, M. H. R. Chakim, Y. Shino, and I. N. Hikam, "Business relationship in business process management and management with the literature review method," *ADI Journal on Recent Innovation*, vol. 5, no. 1Sp, pp. 45–53, 2023.

[15] S. R. Ramzani, P. Konhaeusner, O. A. Olaniregun, A. Abu-Alkheil, and N. Alsharari, "Integrating ai-driven green finance strategies for sustainable development: a comparative analysis of renewable energy investments in germany and denmark," *European Journal of Business and Management Research*, vol. 9, no. 2, pp. 43–55, 2024.

[16] N. M. Nguyen, M. M. Abu Afifa, V. Thi Truc Dao, D. Van Bui, and H. Vo Van, "Leveraging artificial intelligence and blockchain in accounting to boost esg performance: the role of risk management and environmental uncertainty," *International Journal of Organizational Analysis*, 2025.

[17] A. E. Widjaja, M. Mulyati, D. Supriyanti, I. N. Hikam, F. S. Goestjahjanti, K. Kamar, and J. Nathalie, "Implementation of cloud-based information management to enhance work efficiency in information technology companies," *International Transactions on Artificial Intelligence*, vol. 3, no. 2, pp. 150–160, 2025.

[18] S. Kalogiannidis, D. Kalfas, O. Papaevangelou, G. Giannarakis, and F. Chatzitheodoridis, "The role of artificial intelligence technology in predictive risk assessment for business continuity: A case study of greece. risks 12: 19," 2024.

[19] K. Du, Y. Wei, and S. Jin, "Can artificial intelligence enhance corporate financial risk-taking capacity? a perspective on innovation resilience and the environment," *Sustainability*, vol. 18, no. 4, p. 1840, 2026.

[20] M. A. Syari, U. Rahardja, T. Wellem, H. D. Purnomo, and R. Buaton, "Iot enabled smart farming system for optimizing crop management using sensors and machine learning," in *2025 4th International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2025, pp. 1–7.

[21] A. M. Zahedi and S. K. Miakhel, "Artificial intelligence in climate finance: Enhancing green investment, carbon risk assessment and capital allocation," *Journal of Asian Development Studies*, vol. 14, no. 4, pp. 12–24, 2025.

[22] B. Velmurugan, S. Saranya, R. Vetrickarthick, N. Asha *et al.*, "Ai-driven predictive analytics for financial risk assessment and smart investment decision-making in global markets," in *2025 IEEE 3rd Global Conference on Wireless Computing and Networking (GCWCN)*. IEEE, 2025, pp. 1–7.

[23] A. Sutarman, E. Kallas, and O. Jayanagara, "The effectiveness of using blockchain technology as a machine learning program," *Blockchain Frontier Technology*, vol. 4, no. 1, pp. 29–34, 2024.

[24] N. L. Rane, M. Paramesha, S. P. Choudhary, and J. Rane, "Artificial intelligence, machine learning, and deep learning for advanced business strategies: a review," *Partners Universal International Innovation Journal*, vol. 2, no. 3, pp. 147–171, 2024.

[25] S. Singh, S. Yadav, A. Singh, Y. J. Krishna, and A. Singh, "Harnessing technology for a sustainable future in finance: the role of artificial intelligence in promoting environmental responsibility," in *Anticipating Future Business Trends: Navigating Artificial Intelligence Innovations: Volume 2*. Springer, 2024, pp. 367–378.

[26] A. Erica, L. Gantari, O. Qurotulain, A. Nuche, and O. Sy, "Optimizing decision-making: Data analytics applications in management information systems," *APTISI Transactions on Management*, vol. 8, no. 2, pp. 115–122, 2024.

[27] Jakarta Investment Centre. (2025) Ai global trends, indonesia's strategy, and jakarta's future potential. Accessed: 2026-05-05. [Online]. Available: https://invest.jakarta.go.id/news/199/ai-global-trends-indonesias-strategy-and-jakartas-future-potential

[28] E. E. Akhigbe, N. S. Egbuhuzor, A. J. Ajayi, and O. O. Agbede, "Designing risk assessment models for large-scale renewable energy investment and financing projects," *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 5, no. 1, pp. 1293–1308, 2024.

[29] N. Rosanna[1] and A. E. W. Hery, "Designing information systems for transaction and production data management," *IAIC Transactions on Sustainable Digital Innovation (ITSDI) The 4th Edition Vol. 2 No. 2 April 2021*, p. 121, 2021.

[30] J. Vespignani and R. Smyth, "Artificial intelligence investments reduce risks to critical mineral supply," *Nature Communications*, vol. 15, no. 1, p. 7304, 2024.

[31] M. D. T. P. Nasution, Y. Rossanty, R. Harahap, A. R. Tanjung, and T. A. M. Nasution, "Technology-driven resource utilization and integration to enhance firm performance," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 268–283, 2026.

[32] Y. K. Al-Haji and S. B. Bakar, "The impacts of innovation attribute, business environment, and risk management on the artificial intelligence investment decision in oman's hydrocarbons industry." *Pakistan Journal of Life & Social Sciences*, vol. 22, no. 2, 2024.

[33] M. Ferrara, T. Ciano, A. Capriotti, S. Muzzioli *et al.*, "Machine learning predictive modeling for assessing

climate risk in finance," *WSEAS Transactions on Environment and Development*, vol. 20, pp. 852–862, 2024.

[34] D. Juliastuti, E. Alexandrina, E. Sana, R. N. Muti, and G. P. Cesna, "Integrating artificial intelligence for academically challenged students education and health," *International Transactions on Artificial Intelligence*, vol. 4, no. 1, pp. 13–24, 2025.

[35] V. Akash and R. Kumari, "The role of artificial intelligence in promoting sustainable and responsible investments," *Journal of Social Review and Development*, vol. 4, no. Special Issue 1, pp. 182–186, 2025.

[36] R. Z. Ikhsan, S. Rahayu, A. H. Arribathi, and N. Azizah, "Integrating artificial intelligence with 3d printing technology in healthcare: Sustainable solutions for clinical training optimization," *ADI Journal on Recent Innovation*, vol. 6, no. 2, pp. 99–107, 2025.

[37] W. Li, J.-P. Li, Y.-F. Wang, and S.-E. Stan, "Is artificial intelligence an impediment or an impetus to renewable energy investment? evidence from china," *Energy Economics*, vol. 147, p. 108550, 2025.

[38] A. M. Fernández, "Artificial intelligence–driven transformation of investment, corporate strategy, and economic growth: Integrating esg, portfolio management, and technological ecosystems," *Library of Frontline Marketing, Management and Economics Journal*, vol. 6, no. 01, pp. 1–5, 2026.

[39] D. Hernandez, L. Pasha, D. A. Yusuf, R. Nurfaizi, and D. Julianingsih, "The role of artificial intelligence in sustainable agriculture and waste management: Towards a green future," *International Transactions on Artificial Intelligence*, vol. 2, no. 2, pp. 150–157, 2024.

[40] T. Varghese, M. Paranjape, S. Bhome, M. Bhadkamkar, and A. Gupta, "Harnessing artificial intelligence for optimizing green investment portfolios and esg scoring," in *International Conference on Sustainable Computing*. Springer, 2025, pp. 699–711.

[41] M. Nallakaruppan, H. Chaturvedi, V. Grover, B. Balusamy, P. Jaraut, J. Bahadur, V. Meena, and I. A. Hameed, "Credit risk assessment and financial decision support using explainable artificial intelligence," *Risks*, vol. 12, no. 10, p. 164, 2024.

[42] N. Rane, "Integrating leading-edge artificial intelligence (ai), internet of things (iot), and big data technologies for smart and sustainable architecture, engineering and construction (aec) industry: Challenges and future directions," *Engineering and Construction (AEC) Industry: Challenges and Future Directions (September 24, 2023)*, 2023.

[43] S. M. Popescu, S. Mansoor, O. A. Wani, S. S. Kumar, V. Sharma, A. Sharma, V. M. Arya, M. Kirkham, D. Hou, N. Bolan *et al.*, "Artificial intelligence and iot driven technologies for environmental pollution monitoring and management," *Frontiers in Environmental Science*, vol. 12, p. 1336088, 2024.

[44] A. A. A. Chowdhury, A. H. Rafi, A. Sultana, and A. A. Noman, "Enhancing green economy with artificial intelligence: Role of energy use and fdi in the united states," *arXiv preprint arXiv:2501.14747*, 2024.

[45] S. S. Goswami, S. Mondal, S. Sarkar, K. K. Gupta, S. K. Sahoo, and R. Halder, "Artificial intelligence-enabled supply chain management: Unlocking new opportunities and challenges," in *Artificial intelligence and applications*, vol. 3, no. 1, 2025, pp. 110–121.

[46] A. Adefemi, E. A. Ukpoju, O. Adekoya, A. Abatan, and A. O. Adegbite, "Artificial intelligence in environmental health and public safety: A comprehensive review of usa strategies," *World Journal of Advanced Research and Reviews*, vol. 20, no. 3, pp. 1420–1434, 2023.

[47] F. S. Islam, "Artificial intelligence-driven optimization and decision support for integrated waste-to-energy systems in climate-vulnerable megacities: a case study of dhaka, bangladesh," *International Journal of Applied and Natural Sciences*, vol. 3, no. 2, pp. 01–34, 2025.

[48] S. Vudugula, S. K. Chebrolu, M. Bhuiyan, and F. Z. Rozony, "Integrating artificial intelligence in strategic business decision-making: A systematic review of predictive models," *International Journal of Scientific Interdisciplinary Research*, vol. 4, no. 1, pp. 01–26, 2023.

[49] I. Jackson, D. Ivanov, A. Dolgui, and J. Namdar, "Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation," *International Journal of Production Research*, vol. 62, no. 17, pp. 6120–6145, 2024.

[50] S. Mashetty, S. R. Challa, B. ADUSUPALLI, J. Singireddy, and S. Paleti, "Intelligent technologies for modern financial ecosystems: Transforming housing finance, risk management, and advisory services through advanced analytics and secure cloud solutions," *Risk Management, and Advisory Services Through Advanced Analytics and Secure Cloud Solutions (December 12, 2024)*, 2024.