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AI-Driven Sustainable Banking: Examining the Role of Artificial Intelligence in Green Credit Assessment

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Abstract

Despite the potential of artificial intelligence to revolutionize green credit assessment, little information exists on its application in sustainable banking. The present research aims to explore the ways in which AI approaches can be used to factor in environmental risks in loans. The first identified research gap lies in a scarcity of empirical analyses concerning the inclusion of climate risk measurement through AI algorithms alongside more traditional credit score inputs. Utilizing literature across academia and industry (from 2015 to 2026), this section synthesizes empirical findings on climate finance, ESG scores, and AI-driven risk assessment. Empirical findings include evidence that the use of AI allows banks to punish greenwashing firms and that a higher proportion of green loans may lower NPLs. In doing so, the progress made in the field is juxtaposed against traditional approaches and described in terms of data collection (such as company reports and satellite data) and feature extraction. A framework for AI-driven lending is outlined in terms of how capabilities (including big data and machine learning) may enable climate risk evaluation and better loaning decisions. Finally, we provide an overview of an empirical methodology for utilizing AI in the lending process. This includes data gathering, from structured financial and ESG metrics to unstructured sources such as satellite images and textual analysis, alongside model training and dual metric evaluation (credit risk and environmental performance). Explainability methods are incorporated throughout the framework.

Keywords: Artificial Intelligence, Green Credit Assessment, Sustainable Banking, Climate Risk, ESG Scores, Machine Learning, Green Finance, Explainable AI

1. Introduction

Climate change and other environment-related issues have been identified by banks as critical credit risks. The objective of sustainable banking is to incorporate environmental goals into lending but such environmental dimensions are rarely considered in traditional credit assessments. With respect to green credits which are made for the explicit purpose of environmental sustainability, their number has increased considerably (such as the case in China where the value of green credits stood at CNY 22.3 trillion in 2022, representing a 38.5% YoY increase). Evidence regarding the environmental impacts and profitability of green credits is inconclusive. Environmental assessment of loan applicants poses further challenges.

Artificial Intelligence (AI) the means to achieve this by analysing atypical data and modelling intricate patterns. For instance, using machine learning (ML) to combine satellite pictures, climate metrics, and business statements to evaluate a borrower's ecological impact or susceptibility to climate events can be helpful. Large language models (LLMs) can be used to discover indicators of underlying risks from sustainability reports. This is depicted in Figure 1 (below) showing various AI applications in financial risk analysis areas like credit risk and climate risk. Research in risk analytics reveals that ML-based methods (such as random forests and gradient boosting algorithms) tend to perform better than linear models in predicting loan defaults. Climate-specific AI research (for example, Bansal et al. in) demonstrates that deep learning enhances the quantification of climate risks.

Figure 1: *Conceptual domains of AI in financial risk management (credit, market, trading, climate). AI can capture nonlinear relationships and novel indicators (e.g. satellite data) in these areas. [Image: Discover Sustainability 2026]*

Nevertheless, few studies have been done on applications of AI to green credit evaluation. The vast majority of studies of artificial intelligence in financial sectors are concentrated on credit risk assessment and portfolio management issues. Only few works have experimentally used artificial intelligence in evaluating the environmental credit criteria of companies. For example, Zheng et al. (2026) found in their research that loan agreements in China show that banks using artificial intelligence charge higher spreads from companies exhibiting signs of greenwashing. Yet, there are few papers on this topic. Thus, the research question is how AI models can be assessed for environmental risk?

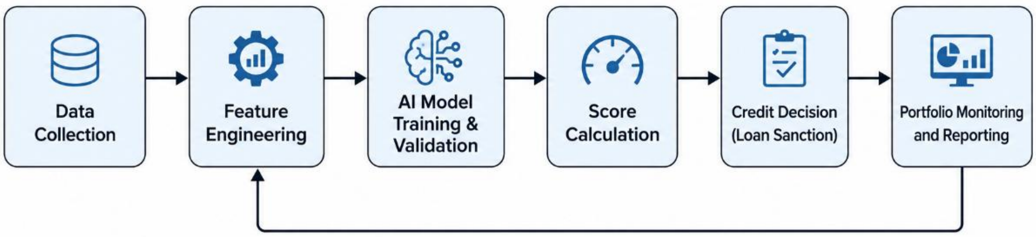
This paper bridges this research gap through a synthesis of the literature, concept modelling, and methodological design. This is done as follows. Firstly, we conduct a review of current AI research in sustainable finance, focusing particularly on green credit and ESG rating research (Section 2). We list the main contributions in terms of their methodologies, findings, and weaknesses. Secondly, we introduce an extensive AI-driven methodology for green credit analysis (Section 3). This involves specifying input data (financial reports, ESG databases, remote sensing satellite data, regulatory reporting), feature engineering procedures, potential AI models (including machine learning and natural language processing models), validation processes, and measures to evaluate AI performance in terms of financial and environmental outcomes. Explainability and fairness are important considerations, given the current trend in regulation.

Thirdly, we introduce our conceptual model (Figure 2). In Section 4 below, we examine the key challenges associated with the implementation process, which includes problems with data quality, lack of transparency in model performance, compliance issues in relation to green finance requirements, potential algorithmic bias, and implementation into banking operations. We also provide possible solutions to these issues. In our concluding remarks (Section 5), we propose concrete suggestions for financial institutions and regulators, as well as highlight future research directions.

Our paper contributes to the literature on integrating green lending practices within banking institutions through a human-cantered AI-based credit risk model. This approach becomes important because of the need to adapt credit risks to climate-related challenges.

1.1 Key AI-Based Green Lending Diagrams

In order to illustrate the mechanics and architecture of the AI-powered green credit scheme, we supplement the original flow chart with more detailed illustrations. Here we have the basic flow of pipeline that will be further elaborated on.



This is the workflow of this process: (A) gather varied data (explained further below), (B) design predictive features, (C) train and test the AI models, (D) score the environmental/credit risks, (E) decide on loans, and (F) measure performance. The following describes data and features (Figure 3) and evaluation/governance workflow (Figure 4).

1.2 Data Sources and Features (ER Diagram)

An AI credit model for environmental risk uses heterogeneous inputs. Figure 3 maps major data domains to features via an Entity-Relationship style diagram.

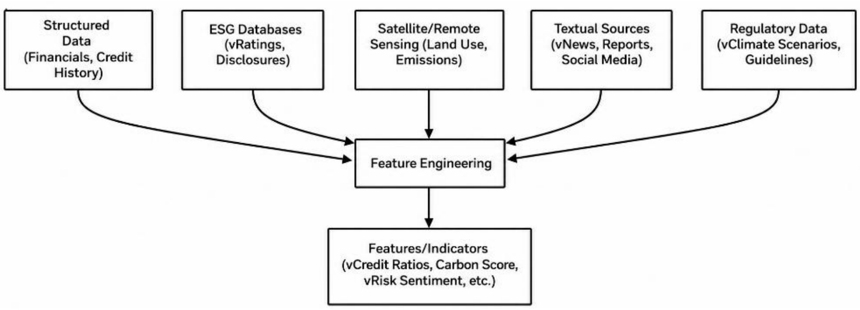


Figure 3: *Key data sources (structured, unstructured, regulatory) and their flow into feature engineering to produce model inputs (features).*

• **Structured data** Borrower's financial statements, collateral valuations, history of performance, and disclosure of ESG by ratings agencies can be considered structured data.

• **The ESG databases** like MSCI, Refinitiv offer scoring of the companies on environmental, energy usage, emissions of pollutants, among others.

• **Satellite data** helps in geospatial analysis, which includes factors like deforestation, growth of crops, emissions from factories. Some studies show that satellites can help lenders in monitoring both crop yields and environmental collateral.

• **Textual sources** include news, regulation, and even social media comments on the borrowing company or industry. NLP techniques can extract relevant information, such as mentions of environmental infringements.

• **Regulation** includes climate stress tests and carbon pricing strategies. These contextual indicators may be used to develop scenario-based stress tests.

This phase will convert these raw inputs into measurable indicators such as financial ratios, credit scores, carbon or climate risk score, composite features of ESG, sentiment scores derived from text analytics, etc. For instance, the use of satellite images could produce a measure of yield variation within agriculture, linked to loan risk. This is then fed into training AI algorithms.

1.3 Model Evaluation & Decision Governance (Flow)

Figure 4 outlines the post-training process of evaluating the model and integrating it into the credit decision governance structure.

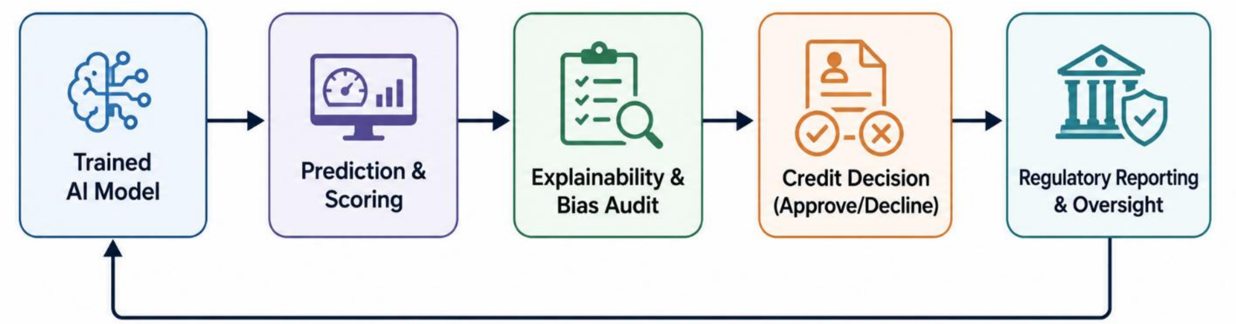


Figure 4: *Flow of model output through explainability checks, decision, and oversight.*

The AI algorithm (M) generates risk assessments (P) based on loan applications (risk scores related to environmental factors, and default risks). Prior to executing the recommendations provided by the algorithm, an oversight mechanism (A) performs explainability and fairness assessment checks (for example, with SHAP values or LIME). Only after that does the risk assessment drive the decision about the loan (approval, rejection, changes to terms and prices). Outcomes of actions and risk assessments are tracked as part of compliance procedures (R). Feedback from results back into the algorithm via the path R → M implies that learning based on outcomes (actual defaults, performance of stress tests) will occur.

2. Literature Review

The following represents a summary of relevant literature (between 2015 and 2026) on the application of AI in sustainable banking and green credit. The summary concentrates on research findings and methodologies. Table 1 provides an overview of the selected sources.

Table 1: Key studies on AI/ESG in credit risk and sustainable finance (2015–2026).

Source (Year)	Type	Methods	Key Findings	Relevance
Zheng et al. (2026)	Empirical (Journal: IRFA)	Loan contract dataset (China, 2019–23); regression on interest spreads, AI-adoption dummy	Banks using AI impose higher spreads on firms with "greenwashing" indicators; effect stronger for ESG-savvy banks and clean firms. Mechanisms: AI improves risk identification and legitimacy.	Shows AI can help detect unreliable green claims and adjust pricing.
Li & Chen (2024)	Empirical (MDPI Sustainability)	Panel data (127 Chinese banks, 2007–22); regression controlling FinTech index	Green credit (loans to eco-projects) significantly *improves* bank performance; higher FinTech adoption (incl. AI) amplifies this effect (via cost reduction, reputation, risk mitigation).	Indicates technology (FinTech/AI) enhances positive impact of green lending.
Bonacorsi et al. (2022)	Empirical (FEEM Working Paper)	Cross-sectional ML analysis (European listed firms); LASSO, Random Forest on Altman Z-score	Incorporating ESG factors (from MSCI) alongside financial ratios improves prediction of firm default risk; identifies which ESG factors most affect credit risk.	Demonstrates ML can quantify ESG contributions to creditworthiness.
Giudici et al. (2025)	Theoretical/Conceptual (Frontiers AI)	Proposed ML framework; ensemble models on hypothetical credit dataset with ESG scores	Proposes ensemble ML models to capture nonlinear effects of ESG on credit ratings; claims AI can reveal latent ESG-credit relationships.	Provides model design principles for ESG-enhanced credit scoring.
Al-Qudah et al. (2023)	Empirical (Env. Sci. Pollut. Res.)	Panel regression (23 UAE banks, 2015–20)	Higher green loan ratio significantly reduces non-performing loan ratio. Bank size, inefficiency affect NPL. Suggests green credit policy improves credit quality.	Evidence that green lending correlates with lower credit risk (NPL).
Hasri et al. (2025)	Empirical (Future Business J.)	Regression (polluting firms, China, post-2012 Green Credit policy)	Strong corporate ESG performance leads to more bank lending and lower borrowing costs, especially for small and non-SOEs. Explains through better info transparency.	Shows ESG metrics directly influence lending decisions under green credit guidelines.

Source (Year)	Type	Methods	Key Findings	Relevance
Caldecott (2022)	Empirical (Wiley Res. Paper)	Panel regression (41 Chinese banks, 2007–18)	The effect of green lending on bank credit risk depends on bank type: for large state banks, more green loans *reduced* risk; but for smaller banks, risk increased (due to expertise gaps).	Highlights how knowledge asymmetries affect green credit outcomes.
Wang et al. (2024)	Survey/Review (WJARR)	Literature and case review; discusses AI in green finance domains	AI automates green bond verification (satellite, NLP) and ESG analysis (NLP on disclosures), but greenwashing and data consistency remain challenges.	Illustrates AI use cases (green bonds, carbon markets) and limitations.
Bisi et al. (2026)	Review (Discover Sustainability)	Survey of AI in sustainable finance (2019–2025)	Identifies AI risk domains (credit, climate risk, ESG evaluation). Concludes AI improves prediction but interpretability is a challenge; calls for interdisciplinary frameworks.	Provides comprehensive context on AI + sustainability including credit.
Caribou Digital (2018)	Case study / Industry	Qualitative case (Fintechs in Kenya)	Satellite imagery used to assess crop health and predict repayment for smallholder loans. Lenders reduce costs and include more customers via ML on remote-sensing data.	Example of unstructured data use (satellite, ML) in agricultural credit.
UNEP-FI (2023)	Industry report	Survey of banks' climate risk practices	Banks are beginning to integrate climate risk outputs into credit decision processes (adjusting ratings, requiring mitigation plans, aligning pricing to exposure).	Shows industry trend to embed environmental risk in credit policies.
Bundesbank (2024)	Press release (AI Initiative)	Proof-of-concept (LLMs for climate data)	Project Gaia used large language models to extract emissions, green bond, and net-zero data from corporate reports, automating climate risk assessment across firms.	Demonstrates AI (LLMs) for parsing ESG disclosures to support risk analysis.

A series of empirical studies provides strong evidence indicating that including sustainable information improves credit decision-making. In particular, several studies demonstrate the importance of ESG indicators in predicting outcomes with significant forecasting power. For instance, Bonacorsi et al. utilize supervised machine learning to demonstrate the usefulness of ESG scores for the purpose of default prediction. Furthermore, Hasri et al. provide evidence indicating that higher ESG scores encourage banks to lend more and under better conditions. This indicates that the environmental record is value-relevant in making credit decisions.

On the other hand, research related to AI has been largely conceptual in nature (see [28], [32]). In this regard, Giudici et al. outline the algorithms for "sustainable AI" through explicitly identifying connections between ESG and credit ratings. The case of Caribou demonstrates a practical application of ML techniques on satellite imagery. Additionally, Yang et al. (2026) empirically demonstrate how AI can be used to detect greenwashing cases.

Methodologies employed methods used include econometric regressions as well as machine learning. Panel regressions and two-step regressions are common when conducting empirical analysis on banks/ firms. Machine learning employs approaches such as random forest, LASSO, gradient boosting, and neural networks, accompanied by cross-validation techniques. Explainability approaches such as SHAP are relatively new in this area. Almost all papers evaluate only financial variables (defaults, spread, and profits), while very few analyse environmental variables.

2.1 Gaps and trends

There is obviously a gap regarding further experimental studies in AI credit tools testing. Almost all reviewed works belong to observational and simulation studies. Another gap revealed in literature concerns the lack of uniformed evaluation approaches that would connect AI predictions and ESG results obtained during a long period. Another issue discussed in literature is data deficiency: ESG scores may vary and data about small firms could not always be available. This is why our method takes into account quantitative and big data sources.

Lastly, the aspect of fairness and governance is mentioned in the review but not measured quantitatively. In this regard, the aspect of transparency is highlighted by Aldemir and Uysal, while regulators such as the ECB/NGFS highlight scenario analysis. In this regard, we adopt the approach by incorporating a transparency layer within our pipeline (See Figure 4).

Nevertheless, the literature provides some indication that AI can be used in the assessment of green credit. In the following Sections 3–5, an overall approach will be developed that integrates the above findings and seeks to address the empirical void using AI.

2.2 Proposed Methodology

An empirical approach to creating an AI-based green credit rating system is described here.

2.2.1 Data Needs

One major challenge is obtaining a multivariate dataset that encompasses information about credit and the environment. Essential elements are:

- **Financial and Borrower Data (structured):** Conventional credit information including balance sheet, income statement, credit score, and collaterals. Demographics and industry type of the borrower. Regulatory information including the purpose codes used for identifying "green" loans. This information is typically available in the database of banks and credit agencies.

- **Semi-structured ESG Rating and Sustainability:** ESG rating information gathered either through the rating firms (such as MSCI and Sustainalytics) or based on self-reporting by measuring ESG ratings. Environmental indicators such as CO2 emissions, water usage, energy usage, and waste generation. Proxy indicators can be constructed when needed, such as emissions intensity per product produced.

- **Unstructured Information via Satellite Remote Sensing:** For the relevant portfolio of the loan, remote sensing information would be useful in constructing environmental indicators. Examples of the indicators include NDVI to assess the productivity of agriculture, nighttime luminosity to measure industrial activity, and SAR imaging to measure deforestation.

- **Textual Data (unstructured):** Company sustainability reports, articles from media outlets, regulations. NLP can be applied to identify risk signals (example: "regulation violation", "climate"). Here we will need data from news sources and social media.

- **Structured Regulatory** and Geospatial Data: Climate-related location indicators (risk of flooding, temperature forecasts). Regulations related to carbon pricing/green tax regime status. It makes sure we are in line with macro stress scenarios (NGFS pathways).

In actual implementation, this calls for a combination of data warehousing. This is because, for instance, modelling the manufacturing loan would entail integrating the company's ratios along with the carbon emissions, regional climate risk factors, and any previous environmental violations.

Sample size and granularity: We consider that there is a large dataset for loan applications or contractual loans (minimum thousand observations). Since climate risk changes gradually, the time period covered in the dataset must be several years (like 2015 to 2025). Breadth across the cross-section will help with generalization (industries, geographies). In case such information is not available internally, syndicated information provided by several banks can be considered.

2.2.2. Feature Engineering.

Key steps to turn raw inputs into model-ready features:

- **Financial Attributes:** Convert financial variables like debt equity and interest coverage into ratios. Normalize by size of company.

- **Environmental Attributes:** Calculate indices like carbon intensity (carbon emissions divided by revenue) and energy efficiency (energy consumption divided by output), or other pollution indices. If satellite imagery is used, employ techniques of computer vision and spectral analysis to measure tree cover loss, crop yield changes, etc.

- **Conflation of Risk Factors:** Develop risk scores for multiple domains, such as environmental risk scores that aggregate information on carbon intensity, exposure to climatic threats, and ESG scores using appropriate weightings.

- **Temporal Features:** Introduce time trends such as year-on-year trends in emissions to identify any improvement/worsening in behaviour.

- **Contextual Controls:** Sector dummies (e.g. heavy industries versus services), interest rates, commodity prices, among others, to separate out environmental influences.

It is essential to have normalization and handling of missing values at all times. Missing ESG scores can be imputed, or surrogate variables like industry averages can be used. Categorical variables like the industry codes can be one hot-encoded or embedded.

2.2.3. Candidate AI Models.

Both classical ML and modern AI techniques are applicable:

- **Supervised Learning:** Classification/Regression using conventional techniques for baseline models. Such techniques work fine with tabular data and are also interpretable.

- **Neural Networks:** Neural Networks can be feed forward or convolutional. They will work well with more complicated patterns, particularly when there are many features. They may even process time-series environmental data.

- **Ensembles:** Ensemble approaches for stacking or voting models.

- **Natural Language Models:** In case of textual data, NLP approaches (such as transformers, LSTM) could be used for encoding texts in feature space or classification of loans based on sentiment towards climate change. It seems appropriate to use embeddings obtained via BERT-like LLM models according to the recommendations by Project Gaia.

- **Unsupervised/Anomaly Detection:** "truly green" exceptions would probably be infrequent, such an unsupervised approach could help identify anomalous environmental characteristics as potential red flags.

- **Hybrid Approach:** Combining rules-based filtering with quantitative machine learning. E.g., if the loan qualifies as "green-certified," then this could serve as a screening criterion.

- **Rationale:** Decision tree-based approaches (Random Forests and Gradient Boosting) are very robust in dealing with mixed type of variables and can perform well in credit scoring related applications. The neural network approach may work well with non-linear combinations of ESG and financial variables. NLP may work well with narrative data.

2.2.4. Validation Strategy.

We recommend a rigorous evaluation protocol:

- **Train/Test Split**: Allocate a validation dataset that acts as a proxy for future loan data. When working with data over time, ensure you do chronological splitting.

- **Cross-validation of Training Dataset:** Use k-fold cross-validation to tune the hyperparameters. If there is an imbalanced ratio of defaults in your data, consider doing stratified folds of CV.

- **Time Series Approach Evaluation:** If using time-series analysis for default probability, try rolling origin validation, considering economic fluctuations within each period.

- **Simulation testing:** Evaluate the performance of the model in certain scenarios, evaluating its robustness under varying environmental conditions. This is similar to stress testing by regulators.

We will track stability of performance across segments (sectors, loan sizes) to detect biases.

2.2.5. Evaluation Metrics.

We use both financial and environmental benchmarks:

- **Financial metrics:** ROC-AUC and Precision and Recall on default prediction; accuracy of decision classification on credits. The profit/loss or risk-adjusted returns could be used for economic assessment of a hypothetical credit portfolio.

• **Environmental metrics**: Classification accuracy of green vs. brown portfolios if labelled data is available; calibration between the predicted and actual carbon footprints. The Aggregate Emission metric for a loan portfolio may be introduced and assessed based on AI's recommendation changes.

• **Joint metrics:** We suggest a new credit scoring model that will incorporate prediction of default risk and risk related to environmental hazards. Efficiency of this modelling technique will be determined based on the possibility of placing higher-ranking risky customers into higher positions. For example, one may apply Score = α*(default probability) + (1-α) *(environmental risk).

• **Performance indicators for interpretability:** Metrics used to determine explainability (surrogate trees quality, etc.) The assessment needs to make clear the comparison between the AI method and a traditional approach that would serve as the baseline (such as logistic regression using financial attributes only).

2.2.6. Explainability and Fairness.

With the focus being on sustainability and accountability, the following will be considered:

• **Feature Attribution:** Employ SHAP or LIME to determine the key features (e.g., emissions, sectors) behind each decision. This will ensure the model actually incorporates environmental data.

• **Simple Model:** Incorporate a simple rule (e.g., "if carbon score exceeds threshold, then conduct extra assessment") into the decision-making process.

• **Fairness Checks:** Conduct disparate impact analysis across demographic/geographic groups (like small businesses vs. big businesses, or developed locations vs. developing locations). Because climate risks can also include geographic factors, it is necessary to be careful not to discriminate when making decisions regarding the denial.

• **Governance:** The need for documenting the rationale behind the model along with decision logs needs to be ensured. Follow the "Responsible AI" approach: SAFE (Security, Accuracy, Fairness, Explainability)).

• **User Interface:** The credit officer must be shown, in addition to the model score, an explanation (for example, "high risk of default due to poor liquidity and 50% above industry carbon intensity").

This methodology establishes a comprehensive empirical testbed. The methodology is supposed to be jurisdiction-agnostic (no specific country). The taxonomy, among other regulations (EU regulations), would be considered as an input rather than an obstacle. In the next section, these components will be integrated into a framework.

3. Conceptual Framework

The above diagram illustrates the postulated linkages among the variables in the study framework. AI ability influences risk assessment and finally results in lending decisions.

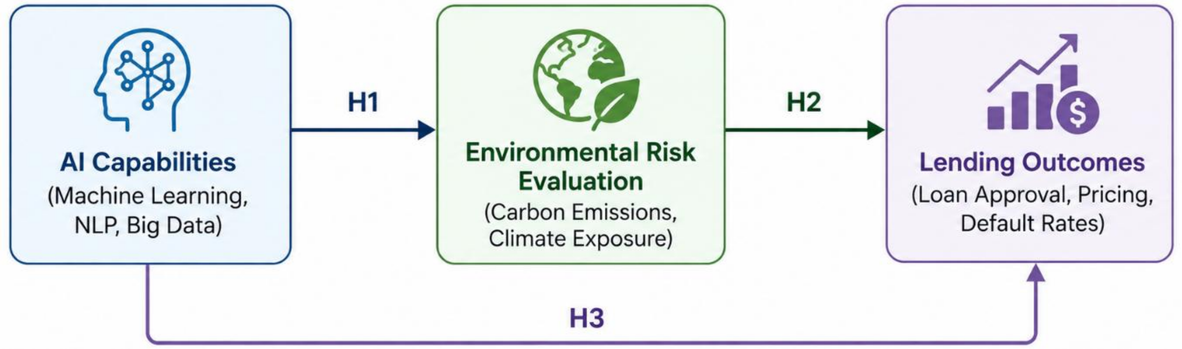


Figure 2: Conceptual framework linking AI abilities to environmental risk assessment and lending results. Arrows indicate hypothesized causal paths (H1–H3).

• H1 (AI → Risk Evaluation): Our research assumes that sophisticated forms of AI will provide an opportunity to increase the precision and detail with which risks can be assessed. For instance, according to H1, machine learning models and natural language processing can derive more accurate and useful risk factors (B) from available data than conventional approaches.

• H2 (Risk Evaluation → Lending Outcomes): Improvement in risk assessment will result in better decision-making with regard to loans. In case the risk of environmental factors (B) is known with certainty, banks can modify their loan practices by approving fewer risky projects, offering high-interest rates for firms involved in carbon-based activities, and so on. This approach is supported by empirical results about ESG.

• H3 (Direct AI → Outcomes): Alternatively, AI can also directly impact the results, such as by programming automated decision-making rules and portfolio surveillance. It is because, in such cases, AI changes the entire process of lending by automating some processes (for instance, approval for lower-risk customers).

The framework shows how interventions at the AI level could have effects that eventually flow into the green lending impact at the bank level. The tests for these hypotheses would involve comparing AI-intervened outcomes with baseline outcomes. For example, do loans from banks in the AI regime demonstrate less aggregate carbon intensity without higher default losses?

4. Implementation Challenges and Mitigation

However, using AI in green lending entails various real-world issues. Some of these include:

• **Quality and Accessibility of Data:** The data on ESG factors is limited and often inconsistent. There is also noise in the form of cloud cover in satellites. Possible solutions could be creating data pipelines, working with data vendors like satellite analytics vendors, implementing data cleaning (to get rid of outliers), and using proxy variables (when there is no firm-level data, industry averages can work).

• **Model Explainability:** Deep neural networks and machine learning ensembles fall into the realm of complex AI. Regulators and loan officers require a degree of transparency in their operations. As mentioned earlier, the solution to the above challenge would be in adopting explainable models wherever possible and making use of post hoc explanation techniques. It is necessary for the model's decision process to be well documented.

• **Regulatory Compliance:** Constraints on models from financial regulations (Basel framework, IFRS 9) and developing climate guidelines (NGFS, EU taxonomy) include, for example, the model that would efficiently exclude high-carbon companies since it may give rise to ethical issues related to fairness or competition. Banks need to make sure that the use of the AI technology satisfies certain criteria, such as those defined by the EU AI Act (which require certification of high-risk AI technologies).

• **Bias and Fairness:** Historical biases may be embedded in AI systems. With respect to green financing, there may be biases against certain geographical locations or sectors that have a high environmental impact. Fairness auditing is important since it compares approval rates for loans between different groups. The application of methods such as reweighting and counterfactual fairness is possible if any biases are found.

• **Operational Integration:** The incorporation of AI tools within the existing credit systems will require a process redesign. Interfaces must be developed to enable the inclusion of the AI scoring alongside the traditional scoring parameters for the loan officers. Training of the employees is essential. We recommend the gradual implementation process for the AI tool.

• **Long-Term Maintenance:** As environmental risks change (due to changing regulations, climatic conditions), models need to be updated periodically with fresh data. The governing body must plan to have the models updated periodically (for instance, quarterly).

Banks would therefore be able to facilitate their transition into the use of AI technologies by being prepared ahead of time. For example, when working together with both data scientists and risk managers, the development of a model can meet all necessary requirements. The Gaia project is an example of how central banks implement AI in climate risks.

5. Recommendations and Research Extensions

4.1 For Banks:

• **Invest in data infrastructure:** capability to integrate ESG data and other non-traditional forms (such as satellite or IoT data). Collaborate with fintech firms/data providers to leverage environmental data.

• **Consider pilot projects:** Deploy AI initiatives in an incremental manner (for example, agricultural loans and climate-exposed mortgage loans). Use experiments for model validation.

• **Employ explainable AI technology:** Include AI tools in the credit decision process to document model-based decisions and allow human intervention if necessary. This will create confidence among management and regulatory bodies.

• **Support strategy:** Use findings from AI to make informed green lending policies. For example, if the risk assessment indicates that there is a high probability of flooding due to climate change in coastal real estate loans, banks can reduce their exposure to such assets.

4.2 For Regulators:

• **Set standards for ESG data:** Encourage frameworks that ensure good quality data on ESG performance (such as climate risk assessments and verified emissions). Standardization is crucial (example in China: Green Credit Guidelines).

• **Establish AI guidelines for green finance:** Provide guidance on incorporating sustainability considerations as legal basis for credit scoring, such as when environmental scores should impact loan terms.

• **Ease stress-testing:** Encourage or mandate climate stress tests for banks; use of Project Gaia might be helpful. Make anonymized data available for model validation by banks.

4.3 Research Extensions:

Potential future research areas could include:

•**Causal effect:** Research into whether AI-based adjustments to loans have an impact on the environment (for example, reduced emissions), through a longitudinal approach.

•**Cross-border examination:** Compare the performance of green credits using AI in different environments (for example, Europe versus Asia), because green concepts and available data differ between countries.

•**Alternate approaches:** Research into other methods such as reinforcement learning in portfolio allocation considering climate change.

•**Human behaviour:** Research the response by the companies knowing that loan terms are affected by the environment.

To conclude, the use of AI can make lending more climate-aware and efficient. The analysis of this report provides a basis on which further development and testing of such green AI-powered credit instruments can be done by both banks and scholars. Through careful consideration of issues with data collection and AI governance, this technology can serve as a driver for sustainable banking practices

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Declaration of Conflicting Interests

I disclose any conflicts of interest that could arise due to this research. The researchers have worked independently, and their personal, professional, or financial connections have not influenced the process of designing, analysing, interpreting, or publishing this article.

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