AI-Enabled ESG Integration in Banking Decision-Making: Governance Implications in European and Emerging Financial Systems

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This study analyses how artificial intelligence (AI) enables the integration of environmental, social, and governance (ESG) factors into banking decision-making and examines its implications for sustainable governance in developed and developing financial systems. The study adopts a qualitative, multi-case comparative design based on the documentary analysis of ESG reports, annual reports, risk management reports, and governance documents from selected banks. The sample includes European banks with advanced AI–ESG integration, namely ING Group, BNP Paribas, Nordea Bank, and NLB Group Slovenia, alongside Raiffeisen Bank Kosovo as a case from a developing financial system. Methodologically, the study employs qualitative documentary analysis through deductive–inductive content analysis, supported by cross-case comparison and selective process tracing, to examine the links among ESG data, AI-based analytics, and financial decision-making. The findings indicate that European banks have more deeply embedded AI and ESG into risk management, lending, and portfolio allocation, supported by stronger governance and control mechanisms. In contrast, banks in emerging financial systems show partial integration, mainly focused on reporting and regulatory compliance. The study highlights the need to strengthen AI governance, transparency, and model risk management to support sustainable banking decision-making.

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1 Introduction

In recent years, integrating environmental, social, and governance (ESG) factors has become a strategic priority for banks, driven by regulatory pressures, investor expectations, and stakeholder demands for a more sustainable financial system. EU frameworks such as the Green Deal, Taxonomy, and Corporate Sustainability Reporting Directive (CSRD) have raised transparency requirements, strengthened sustainability risk management, and embedded ESG into financial decisions. Meanwhile, Artificial Intelligence (AI) and advanced data analytics are transforming how banks analyze risk, assess clients, and allocate capital. Combining AI with ESG data enables more accurate assessment of climate, social, and governance risk, supporting financial institutions' long-term sustainability. However, differences in technological and institutional development between developed and developing financial systems pose distinct challenges for effective AI–ESG integration.

The literature has discussed ESG's role in financial performance and risk management, as well as AI's impact on banking's digital transformation. However, few studies examine how banks integrate AI and ESG in decision-making. Most research examines these areas separately and does not address how advanced analytics embed sustainability in lending, portfolio management, or risk assessment. Additionally, most evidence comes from developed economies; there is a need for comparative studies on emerging financial systems, where data infrastructure, tech capacity, and governance may hinder AI–ESG integration.

In this context, the aim of this study is to analyse how Artificial Intelligence enables the integration of ESG factors into banking decision-making. The study also assesses the implications of this process for sustainable governance in developed and emerging financial systems. Specifically, it aims to identify the main practices for using AI to process and integrate ESG data into decision-making. It further analyzes the role of governance and control mechanisms in managing risks associated with models and analytics. The study also compares the level and depth of AI–ESG integration between European Union banks and a bank in an emerging financial system. The main research question is: How and to what extent does AI contribute to the effective integration of ESG factors into banking decision-making? What are the implications for sustainable governance in different institutional contexts?

This paper provides an integrated view of how digital transformation and sustainable finance interact, linking AI use to governance and risk management in banking. A comparative analysis of mature and emerging financial systems highlights the structural and institutional differences shaping AI–ESG integration. For bank executives and policymakers, the results underscore the need to strengthen AI governance, boost algorithmic transparency, and develop institutional capacity for effective model risk management and sustainable financial decision-making.

This study contributes to the existing literature in three main directions. First, unlike most previous studies that treat artificial intelligence, ESG integration, or sustainable finance separately, this paper analyzes these dimensions in an integrated manner within banking decision-making processes. Second, the study expands the comparative framework to include both European banks with more advanced AI–ESG integration and a case from an emerging financial system, thereby enabling the identification of institutional, technological, and regulatory differences. Third, the paper's original contribution lies in the analytical link between ESG data, advanced analytics/AI, governance mechanisms, and financial decision-making, offering theoretical implications for the literature on sustainable governance and practical implications for bank managers, regulators, and policymakers.

2 Literature Review

The integration of environmental, social, and governance (ESG) factors in the financial sector has intensified significantly in recent years, driven by regulatory pressures, investor demands, and increasing risks related to climate change and sustainability. At the same time, developments in artificial intelligence (AI) and advanced data analytics have transformed the way financial institutions analyze information, assess risk, and support decision-making. Against this backdrop, recent literature has expanded significantly in two main directions: the use of AI to process and assess ESG data, and the impact of these factors on financial performance and stability. Nevertheless, the evidence remains fragmented and often treats AI and ESG as separate fields. To address this gap, this review uses a synthesizing and comparative approach to organize the literature into four main areas: (1) technological approaches to AI in ESG, (2) impact on financial decision-making, (3) governance and regulatory challenges, and (4) existing practices and factors of success or failure.

From a foundational perspective, ESG integration is closely linked to stakeholder theory and the broader evolution of corporate sustainability. Stakeholder theory argues that firms should not be governed solely in shareholders' interests, but should also consider the expectations and interests of wider stakeholder groups, including customers, employees, regulators, communities, and the environment. In the banking sector, this perspective is particularly relevant because financial institutions influence capital allocation, risk distribution, and long-term economic resilience. Therefore, ESG integration can be understood not only as a reporting practice, but also as a governance mechanism through which banks internalize environmental, social, and governance-related risks into strategic and financial decision-making (Freeman, 1984; Eccles et al., 2014).

2.1 Artificial Intelligence - Driven Data Analytics and Technological Approaches for ESG Integration

The literature indicates that one of the main contributions of artificial intelligence to ESG integration is the improvement in the processing, assessment, and interpretation of sustainability-related data. Machine learning models can support ESG rating prediction by combining financial and non-financial indicators, while explainable AI techniques, such as SHAP and ensemble learning, enhance transparency into the factors influencing ESG performance. In addition, the digitalization of sustainability indicators and their integration into big data systems enable more systematic monitoring of environmental, social, and governance risks. These developments suggest that AI can enhance ESG analysis not only by increasing processing speed, but also by improving the consistency, scalability, and interpretability of sustainability assessments (Cini & Ferrari, 2025; Lee et al., 2025; Telukdarie et al., 2024; Zhang & Zhao, 2026; Zhao & Jin, 2025).

At the same time, ESG data remain affected by measurement uncertainty and rating divergence. A key challenge identified in the literature is the inconsistency of ESG ratings across providers, which can weaken the reliability of ESG-based financial analysis and decision-making. This problem is linked to broader debates on ESG measurement, where indicators are shaped by rating methodologies, disclosure quality, sectoral differences, and normative assumptions about sustainability performance. In banking, this creates an important methodological challenge: AI-enabled ESG analysis is only as reliable as the quality, comparability, and governance of the underlying data. Therefore, despite rapid technological progress, there is still limited evidence on how AI-based ESG analytics are translated into concrete banking decisions, particularly in lending, risk management, and portfolio allocation (Berg et al., 2022; Davidescu et al., 2025; Dinaj & Morina, 2025; Morina & Dinaj, 2025).

2.2 The Role of AI - ESG Integration in Financial Decision-Making and Risk Management

The discussion on ESG integration in banking decision-making should be situated within the broader framework of sustainable finance. Sustainable finance emphasizes that financial decisions should incorporate long-term environmental and social externalities, rather than relying exclusively on short-term financial indicators. In this perspective, ESG factors become relevant inputs for credit assessment, investment allocation, risk pricing, and portfolio strategy. For banks, this implies a shift from traditional risk-return analysis toward a broader governance framework that integrates climate risk, social responsibility, and institutional accountability into financial decision-making (Schoenmaker & Schramade, 2018).

Recent studies show that ESG factors are increasingly associated with financial stability, reduced systemic risk, and sustainability-oriented portfolio allocation. In parallel, AI models are being used to improve credit scoring, financial stress analysis, early-warning systems, and explainable decision-making in banking. These developments indicate that AI and ESG can jointly support more informed risk assessment and capital allocation when they are embedded in structured governance and data systems. However, much of the existing literature still examines ESG and AI separately, while fewer studies analyze how AI-enabled ESG analytics are incorporated into banks' strategic and operational decision-making processes (Bouattour et al., 2024; de Lange et al., 2022; Del Fava et al., 2024; Hamdouni, 2025; Hu et al., 2025; Lin & Jin, 2023; Morina & Dinaj, 2024; Morina, 2024; Morina, 2025).

2.3 Governance, Regulatory Frameworks, and Model Risk in AI-Enabled Sustainable Finance

AI governance should be understood through foundational principles of trustworthy and responsible artificial intelligence. These principles emphasize transparency, accountability, robustness, fairness, human oversight, and risk management throughout the AI life cycle. In financial institutions, such principles are particularly important because AI-supported decisions may affect credit access, customer risk assessment, compliance monitoring, and portfolio allocation. Therefore, AI governance is not limited to technological control, but also includes institutional accountability, model validation, explainability, auditability, and alignment with regulatory and ethical standards (OECD, 2019; European Commission & High-Level Expert Group on Artificial Intelligence, 2019).

The growing use of AI in finance has introduced new governance challenges, including model explainability, data protection, algorithmic bias, operational risk, institutional accountability, and regulatory harmonization. These challenges are especially relevant in banking, where AI-based systems can influence lending, risk monitoring, and customer evaluation. Recent literature emphasizes the need for robust control mechanisms, audit processes, responsible AI frameworks, and international regulatory coordination to ensure that AI adoption supports innovation without increasing ethical, regulatory, or reputational risks. However, AI governance and ESG governance are still often discussed separately, leaving a gap in understanding how model risk, ESG reporting, and sustainability-oriented decision-making interact within banking institutions (Ali et al., 2025; Bahoo et al., 2024; Batool et al., 2025; Černevičienė & Kabašinskas, 2024; Emery-Xu et al., 2025; Fundira & Mbohwa, 2025; Pisoni & Moloney, 2024; Ridzuan et al., 2024).

Recent studies further underscore the need for a broader, more integrated understanding of ESG, sustainability indicators, and AI governance in financial decision-making. Circular economy principles can enrich ESG assessment by introducing new sustainability metrics, while quantitative sustainability frameworks help connect environmental, institutional, and social development indicators. In banking, AI is increasingly used to optimize financial operations and support data-driven decision-making, but algorithmic credit decisions also raise concerns about transparency, accountability, and the right to explanation. These studies reinforce the argument that AI–ESG integration in banking should be examined not only as a technological process, but also as a governance, measurement, and accountability challenge (Macher & Szigeti, 2025; Nagy-Rádli et al., 2025; Singh et al., 2025; Lui et al., 2025).

2.4 Implementation Practices, Success Factors, and Structural Barriers in AI–ESG Adoption

Empirical studies on banking-sector practices show uneven levels of ESG and AI–ESG integration across institutions and regions. Banks in more developed financial systems have increasingly incorporated ESG factors into stress testing, risk management, lending policies, and capital strategies. In contrast, in many emerging or less institutionally developed contexts, ESG implementation remains more closely linked to compliance, reporting, and reputational risk management. The literature identifies several critical success factors for deeper integration, including ESG data quality, analytical capabilities, senior management support, governance maturity, and regulatory pressure (Acharya et al., 2023; Garefalakis et al., 2025; Gonzalez-Ruiz et al., 2024; Rania, 2026; Zairis et al., 2024).

From a broader sustainability perspective, green economy indicators and sustainability-oriented financial strategies provide additional tools for assessing long-term performance and institutional resilience. However, comparative studies that examine how AI and ESG are jointly integrated into banking decision-making across developed and developing financial systems remain limited. This gap is particularly relevant because emerging financial systems often face constraints related to data availability, digital infrastructure, regulatory capacity, and external assurance mechanisms. As a result, the depth of AI–ESG integration depends not only on technological adoption, but also on the institutional conditions that allow ESG data and AI-based analytics to influence financial decisions (Elezaj et al., 2025; Morina et al., 2025; Morina & Elezaj, 2025).

2.5 Research Gaps and Positioning of the Study

The literature review reveals three main gaps. First, most studies examine AI, ESG integration, and sustainable finance as separate research domains, while paying limited attention to their combined role in banking decision-making. Second, the governance literature often addresses AI regulation, model risk, or ESG reporting independently, without sufficiently explaining how these dimensions interact in financial institutions. Third, empirical evidence remains concentrated in developed economies, while comparative research that includes emerging financial systems is still limited. This study addresses these gaps by analyzing how AI-enabled analytics support the use of ESG data in banking decision-making and how governance mechanisms shape this process. By comparing selected European banks with a bank operating in an emerging financial system, the study contributes to the literature on digital transformation, sustainable finance, and banking governance by identifying differences in institutional maturity, data infrastructure, and AI–ESG integration.

3 Scientific Research Methodology

This study is built on the epistemological paradigm of interpretivism, which is based on the premise that institutional and organizational reality is not an independent objective entity, but a social construct formed through practices, actors' interpretations, and regulatory context. The integration of artificial intelligence and ESG factors in the banking sector is not merely a technical transformation but a complex institutional process encompassing governance mechanisms, organizational culture, decision-making structures, and regulatory dynamics. In this sense, the interpretivist approach is appropriate for analyzing how banks conceptualize, operationalize, and institutionalize AI–ESG integration across their strategic and operational processes. The study does not aim to test hypotheses in the positivist sense, but to explore the mechanisms and meanings that construct this integration in different financial contexts.

In line with this paradigm, an exploratory multiple-case research design was adopted. The exploratory approach is justified by the fact that joint AI–ESG integration in banking decision-making is a relatively new phenomenon and still understudied in the literature, especially in comparative analyses between developed and developing financial systems. The multiple-case design allows for in-depth analysis within each case and systematic comparison across cases, providing a more complete understanding of institutional, technological, and regulatory variations. Through this approach, the study aims to identify common patterns of integration and structural differences across financial systems at different levels of development. The study is guided by several interrelated research questions. First, it analyzes how artificial intelligence technologies are integrated into the processing and use of ESG data in selected banks. Second, it examines the impact of this integration on financial decision-making and risk management processes. Third, it assesses the governance mechanisms and control structures that support the implementation of AI–ESG. Finally, institutional differences between banks in developed and developing financial systems are identified in relation to this transformation process.

The selection of cases was carried out through a purposive approach, based on criteria related to the level of ESG integration, adoption of digital technologies, and documentary transparency. The cases included from the European Union include ING Group (Netherlands), BNP Paribas (France), Nordea Bank (Finland), and NLB Group (Slovenia), which are known for their advanced engagement in ESG reporting and digital transformation. Raiffeisen Bank Kosovo is included as a case from a developing financial system, which provides a relevant perspective for comparative analysis in a less consolidated institutional and regulatory context. This selection allows exploration of structural differences and technological capacities across contexts.

The study relies mainly on secondary documentary data, which include annual financial reports, ESG and sustainability reports, risk management documents, corporate governance policies, digital strategies, and public regulatory documents. The use of official documentation provides a solid basis for analysis and allows tracking the evolution of AI–ESG integration practices over time. The data were systematically analyzed to identify congruences between strategic discourse and implementation practices.

In the analytical aspect, qualitative documentary analysis was initially applied to identify how banks articulate the integration of AI and ESG in their strategic and operational documentation. Next, a deductive–inductive content analysis was used. In the deductive phase, initial coding was based on theoretical categories derived from the literature, including AI integration, ESG metrics, risk management, and governance mechanisms. In the inductive phase, new themes emerge from the empirical analysis of the documents, expanding the conceptual framework beyond the initial theoretical predictions. This hybrid approach enables a balance between theoretical structuring and openness to empirical evidence.

The coding process was conducted in several sequential stages to ensure transparency and analytical consistency. An initial set of about 12 deductive codes was created, drawn from the literature and the study's research objectives, including AI integration, ESG indicators, risk management, credit decision-making, AI governance, model control, and regulatory transparency. During the systematic reading of bank reports and governance documents, these codes were revised and expanded inductively, identifying new sub-themes such as ESG data quality, the use of proxy indicators, preventing greenwashing, the role of oversight committees, and institutional constraints in emerging financial systems. To increase the reliability of the analysis, coding was carried out iteratively, continuously comparing theoretical categories with documentary evidence and rechecking key-coded fragments to ensure consistency among data, themes, and analytical interpretations. This approach enabled the analysis to move beyond solely descriptive analysis and to identify connections between ESG data, the use of AI/advanced analytics, governance mechanisms, and financial decision-making.

Table 1 presents the methodological clarification of the process of case selection, coding development, analytical validation, and selective use of process tracing to strengthen the transparency and reliability of the qualitative analysis.

Table 1: Clarification of Case Selection, Coding Process and Process Tracing Logic

Methodological component	Clarification added to strengthen methodological precision
Case selection logic	Cases were selected purposively based on three main criteria: ESG maturity, level of AI/digital adoption, and availability of transparent documentary evidence. ING Group, BNP Paribas, Nordea Bank, and NLB Group were selected because they represent European banking systems with more developed ESG governance, digital transformation, and public reporting. Raiffeisen Bank Kosovo was selected to provide a comparative case from a developing financial system with different institutional, regulatory, and technological conditions.
Initial deductive coding	The initial coding framework included approximately 12 deductive codes derived from the literature and research objectives, such as AI integration, ESG metrics, credit decision-making, portfolio allocation, risk management, AI governance, model risk, transparency, regulatory compliance, and institutional constraints.
Inductive refinement	During document analysis, additional inductive sub-themes emerged, including ESG data quality, proxy indicators, greenwashing prevention, committee-level oversight, external assurance limitations and the maturity gap between developed and emerging financial systems.

Methodological component	Clarification added to strengthen methodological precision
Coding validation	Coding was conducted iteratively by comparing coded evidence across reports, revisiting key fragments and checking the consistency between documentary evidence, thematic categories and analytical interpretations. This strengthened reliability and reduced the risk of subjective interpretation.
Selective use of process tracing	Process tracing was used selectively because the study relies on public documentary evidence rather than internal bank data. It was applied only where documents allowed a reasonable reconstruction of the link between ESG data, AI/analytics, risk assessment, financial decision-making and governance oversight.
Evidence for causal links	Causal links were inferred from documentary evidence such as ESG questionnaires, climate risk assessment tools, AI governance committees, model risk controls, data-quality methodologies, sustainability reporting controls and credit decision procedures.

Source: Author's own elaboration based on the methodological design of the study.

After analyzing each case, we conducted a cross-case comparative analysis and identified common patterns and systematic differences. This phase compared levels of AI–ESG integration, the use of analytics in decision-making, and governance mechanisms. To clarify causal links, we applied the process-tracing method selectively to reconstruct how ESG data processing, through AI analytics, informs financial decision-making and governance oversight. This approach highlighted institutional mediations and key control points at each process stage.

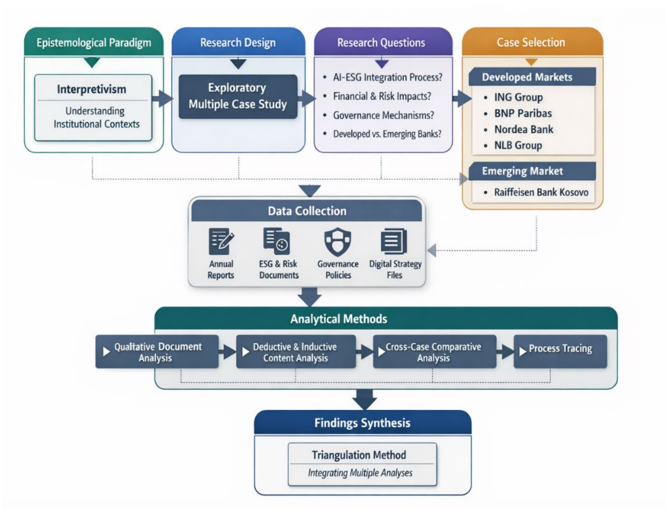

Figure 1: Conceptual and Methodological Framework of the Study
Source: Author's elaboration based on the research design (2026)

Figure 1 shows the methodological framework of the study. It illustrates the logical flow from the epistemological paradigm and exploratory design, through case selection and data collection, to the analytical methods and the triangulation of findings.

To increase the validity and reliability of the findings, methodological triangulation was used, combining documentary analysis, content analysis, cross-case comparisons, and process tracing. Triangulation enabled verification of the consistency of evidence from different sources and reduced the risk of biased interpretation. Through this integrated methodological approach, the study provides an in-depth and systematic analysis of AI–ESG integration in the banking sector, contributing to the understanding of the institutional and structural mechanisms that shape sustainable digital and financial transformation.

4 Results and Findings

4.1 ING Group (Netherlands) – Institutional integration of AI–ESG

ING's annual reporting presents digital transformation, analytics, and AI as organizational capabilities that support value creation, risk management, and operational efficiency. The bank reports using AI and GenAI across several domains, including compliance/KYC, customer service, lending support, and software engineering. It also describes the development of a unified data analytics and AI environment to improve consistency across analytical initiatives, simplify risk assessment, and strengthen data governance (ING Bank N.V., 2025).

From an AI-ESG governance perspective, the most relevant evidence is ING's treatment of AI as both an operational tool and a source of model and regulatory risk. The report links AI use to risks related to data, algorithms, incorrect outputs, bias, privacy, and accountability, and refers to dedicated oversight structures, such as the Central AI Risk Committee, as well as AI-related control mechanisms. Institutionally, ING's reporting indicates a relatively advanced level of AI integration in decision-making processes, while also suggesting that the reliability of AI-supported ESG and risk analytics depends on data governance, model control, and regulatory compliance. Since this interpretation is based on public documentary evidence, it should be understood as an analytically inferred pattern rather than direct verification of internal operational implementation.

4.2 BNP Paribas (France) – Institutional integration of AI–ESG

BNP Paribas presents AI as part of its broader innovation and digital transformation strategy, emphasizing its role in processing large volumes of data, improving efficiency, and strengthening risk management. The group's reporting refers to the industrialization of AI use cases and highlights a cautious approach to GenAI, shaped by regulatory requirements, data security, and responsible AI principles. The existence of a responsible AI charter and strengthened governance infrastructure indicates that AI is treated not only as a tool for operational optimization but also as an area requiring institutional control and regulatory legitimacy (BNP Paribas, 2023).

Additional evidence from BNP Paribas Bank Polska S.A. indicates how this digital transformation is operationalized within the broader group ecosystem through data platforms, GenAI-based tools, chatbots, and software development support systems. These initiatives suggest that AI-enabled analytics are increasingly used to strengthen data-driven processes and organizational efficiency, while also requiring appropriate governance and control mechanisms (BNP Paribas Bank Polska S.A., 2024).

For the purposes of this study, BNP Paribas provides evidence of how AI and advanced analytics can support ESG-related risk assessment and decision-making. The bank's documentation suggests that ESG data may inform client assessment, climate risk analysis, allocation models, and monitoring processes, although the public reports do not fully disentangle all causal pathways between AI use and specific financial decisions. Therefore, BNP Paribas is interpreted as a case where AI-enabled analytics and ESG governance are increasingly connected, but where the depth of operational implementation remains partly inferred from documentary evidence.

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4.3 Nordea Bank (Finland) – Institutional integration of AI-ESG

In the 2025 annual report, Nordea places sustainability reporting within an internal control and risk management framework, where the Group Risk function defines the taxonomy of ESG risk factors and guides the integration of ESG impacts/risks/opportunities into strategy and risk management; the reporting process is monitored by various committees and reported to board committees (e.g., Operations and Sustainability; Audit) (Nordea, 2025). For the AI/analytics component, Nordea's official web resources make the spectrum of operational uses of AI clearer: Nordea describes uses that include "knowledge assistants", "deep analytics" tools, personalization of customer communication, and uses in financial crime prevention (Nordea, 2025). Nordea also presents AI as an enabler for "conversational banking", automation of internal tasks, faster delivery of insights and fraud detection, linking it to the customer experience and increased digital interactions (Nordea, 2025).

Nordea presents an architecture in which ESG is integrated through a "risk taxonomy" and reporting controls, while AI is positioned as a technology layer that improves efficiency, personalization, and protection against financial/operational risks (e.g., financial crime).

4.4 NLB Group (Slovenia) – Institutional integration of AI–ESG

The 2024 Annual Report provides a strong basis for institutional analysis because it clearly documents the sustainability governance architecture and its connection to decision-making structures. NLB describes the existence of board committees (e.g., Audit, Risk, Nomination, Remuneration, Operations, and IT) that participate in sustainability issues, as well as committees dedicated exclusively to sustainability (e.g., Sustainability Committee, Climate Change Committee). The Sustainability Committee is described as a central advisory body to the board of management, which oversees the integration of ESG factors into the business model, validates strategies/policies/methodologies/KPIs, and monitors the achievement of strategic objectives (NLB Group, 2024).

For the AI component, the report establishes board-level oversight through the Operations and IT Committee, with main tasks including monitoring AI use, integrating AI into operations, ensuring compliance with AI regulations, and overseeing key AI projects (NLB Group, 2024). In terms of data governance, the report shows the presence of structures such as the Data Governance Council and IT and product architecture committees, which identify and address the impact of ESG factors within their respective scopes (NLB Group, 2024).

NLB presents a model where AI-ESG integration is "institutionalized" through committees and policies: ESG is anchored in dedicated committees and reporting cycles, the Operations & IT committee with a clear mandate for compliance and accountability. This structure makes the case very suitable for comparative documentary analysis, because the "footprints" of integration are measurable in committee mandates, policy/KPI approval processes, and the way AI governance extends to operations and risk.

4.5 Raiffeisen Bank Kosovo (Kosovo) – Institutional integration of AI-ESG in a developing financial system

Raiffeisen Bank Kosovo primarily integrates ESG through its risk management and lending framework. The 2024 Annual Report links ESG risk appetite, risk management tools, data aggregation, reporting, and ESG integration into end-to-end processes, while also emphasizing the importance of measurement and analytical methodologies. Additional documentary evidence shows that ESG risks are incorporated into financing decisions through exclusion lists, employee training, ESG expert opinions for critical clients or projects, and procedures to prevent negative ESG impacts and greenwashing (Raiffeisen Bank Kosovo, 2022, 2024).

Compared with EU cases, AI-ESG integration at Raiffeisen Bank Kosovo appears more evident through ESG data collection, risk classification, and credit-process controls than through explicit references to advanced AI models. The documents indicate progress toward standardizing ESG definitions and collecting ESG data for larger corporate clients, but provide limited evidence of AI-based analytics embedded in core risk models or portfolio-level decision-making. This suggests that the bank is at an operational-reporting stage of ESG integration, where ESG is increasingly linked to credit rules and risk processes, while deeper AI-enabled decision-making requires further empirical verification.

4.6 Thematic findings from deductive-inductive content analysis

The deductive-inductive content analysis identified four main themes: AI-enabled ESG data processing, ESG integration in financial decision-making, governance and oversight mechanisms, and institutional or structural constraints. In the deductive phase, the analysis focused on predefined categories derived from the literature, including AI integration, ESG indicators, risk management, governance structures, and decision-making processes. In the inductive phase, additional sub-themes emerged from the documents, including ESG data quality, proxy indicators, greenwashing prevention, limitations on external assurance, and the maturity gap between developed and emerging financial systems.

The first theme concerns AI-enabled ESG data processing. The findings indicate that the value of AI in ESG integration depends not only on analytical capacity but also on data quality, methodological transparency, and governance of uncertainty. For example, Nordea's use of PCAF-based financed-emissions methodologies and data-quality scoring illustrates how ESG data uncertainty can be managed through standardized procedures. Similarly, ING's reporting treats AI itself as a governance object, linking AI risks to privacy, accuracy, bias, accountability, and dedicated oversight structures.

The second theme focuses on ESG integration into financial decision-making. The evidence suggests that ESG becomes operationally relevant when it is embedded in lending procedures, client assessment tools, climate risk analysis, stress testing, and portfolio transition strategies. In the case of BNP Paribas, ESG questionnaires and climate risk assessment mechanisms illustrate how ESG indicators can serve as inputs to credit and monitoring processes rather than solely as reporting elements.

The third theme relates to governance and oversight mechanisms. The findings suggest that AI–ESG integration appears more credible and institutionally embedded when supported by committees, mandates, audit processes, model-risk controls, and data governance structures. NLB provides relevant evidence of this pattern, as its reports describe board-level and committee-level oversight of sustainability, IT, and AI-related issues. This indicates that ESG and AI governance increasingly operate as interconnected elements within a broader control architecture.

The fourth theme captures institutional and structural constraints. Across the cases, data availability, regulatory complexity, methodological uncertainty, and external assurance limitations appear as key barriers to deeper AI–ESG integration. These constraints are present even in advanced banking systems, but they are more visible in emerging financial systems, where ESG data infrastructure and external verification mechanisms are still developing.

Table 2: Cross-Case Thematic Findings from Deductive - Inductive Content Analysis

Theme	Deductive Focus	Inductive Refinements Emerging from Documents	Illustrative Documentary Evidence (examples)	Cases where evidenced
Theme 1: AI-Enabled ESG Data Processing	ESG scoring automation; data integration; ML in risk analytics	Data-quality governance; uncertainty management; AI risk as a governance object	PCAF-based financed-emissions methodology with annual ALCO approval and PCAF data-quality scoring (1–5); dedicated AI oversight structures (AI Risk Committee, CoE)	Nordea; ING
Theme 2: ESG Integration in Financial Decision-Making	ESG in credit allocation; portfolio strategy; stress testing	ESG questionnaires as credit instruments; operational ESG “gatekeeping”; transition targets embedded in portfolio shifts	ESG questionnaires used in lending and linked to climate stress-testing logic; portfolio transition targets and reduced fossil exposure framing	BNP Paribas (Group / PL); (contextual implications for other cases)
Theme 3: Governance and Oversight Mechanisms	AI governance structures; model validation; transparency/compliance	Board-level AI oversight integrated with IT/security; sustainability	Supervisory Board Operations & IT Committee mandate: AI infrastructure/use, AI integration,	NLB

Theme	Deductive Focus	Inductive Refinements Emerging from Documents	Illustrative Documentary Evidence (examples)	Cases where evidenced
		reporting audit/controls; double materiality engagement	responsibility, AI rules compliance; sustainability reporting process and external audit references	
Theme 4: Institutional and Structural Constraints	Data availability; regulatory pressure; capability gaps	Proxy use and residual uncertainty; compliance complexity; institutional verification limitations	Explicit treatment of uncertain/estimated ESG emissions data and proxies within PCAF framework; AI governance as response to risk/compliance constraints	Nordea; ING (with broader cross-case implications)

Source: Author's own elaboration based on qualitative document analysis using ATLAS.ti software

The fourth theme synthesizes the institutional and structural constraints that affect the intensity and quality of AI–ESG integration. A first constraint, also present in advanced banks, concerns the availability and quality of data, and documents acknowledge uncertainties and manage them through standardization approaches. At Nordea, the use of proxies and the assessment of data quality through the PCAF score make it clear that uncertainty is not completely eliminated; it is introduced into the methodology and reported as part of transparency. A second constraint is related to regulatory pressure and the complexity of compliance, which conditions the scaling of artificial intelligence by requiring control, demonstrability, and accountability. ING's reporting language, which treats AI risk as an object of governance and associates it with specific oversight structures, shows that the integration of AI into decision-making cannot be understood without the regulatory dimension and without the control of model risk. A third limitation, more pronounced in contexts with limited institutional capacities, relates to external verifiability and assurance infrastructure, which shifts integration towards the phases of database development, harmonized definitions, and consolidated control mechanisms.

In summary, the deductive–inductive content analysis suggests that AI–ESG integration is not a single technology product, but an institutional process that requires data governance, artificial intelligence governance, formalized decision-making instruments, and transparency mechanisms. The differences between cases appear more as differences in the maturity of the institutional architecture than as differences in declarations.

4.7 Cross-case comparative analysis: EU versus emerging financial system

The cross-case comparison suggests that the main difference between the EU banks and the Kosovo case lies not only in the level of technology use, but also in the institutional maturity of AI–ESG integration. In the EU, AI and ESG are more closely linked to risk management, lending procedures, portfolio monitoring, and governance structures. ING and NLB provide evidence of formal AI oversight and model-risk control, while BNP Paribas and Nordea illustrate how ESG data and climate-related indicators are incorporated into credit assessment, monitoring, and portfolio-level analysis.

In contrast, the Kosovo case reflects an earlier stage of integration, where ESG is mainly operationalized through data collection, exclusion lists, ESG expert opinions, greenwashing-prevention procedures, and reporting transparency. These mechanisms are important for institutional development, but the analyzed documents provide limited evidence of AI-based analytics embedded in core credit-risk models or portfolio allocation processes. This indicates a more compliance- and process-oriented form of ESG integration compared with the more formalized governance and analytical structures observed in the EU cases.

Overall, the comparison indicates that AI–ESG integration is deeper where ESG data infrastructure, AI governance, model-risk controls, and external assurance mechanisms are more developed. In emerging financial systems, the priority appears to be consolidating ESG data, standardizing internal procedures, and strengthening verification mechanisms before more advanced AI-enabled decision-making can be fully institutionalized.

Table 3: Cross-Case Comparison (EU Banks vs Kosovo Bank)

Comparative Dimension	EU Banks (ING, BNP Paribas, Nordea, NLB)	Kosovo Bank (Raiffeisen Bank Kosovo)
Depth of AI Integration	AI treated as a material risk and governance object; formal oversight and model-risk controls are emphasised; board/committee-level monitoring exists	Early-stage enablement through ESG data collection and process development; limited evidence of AI embedded in core risk models in the analysed reports
ESG Operationalization	ESG embedded into lending origination/monitoring via ESG assessment questionnaires; climate risk assessed within lending and linked to stress testing; portfolio-level emissions data consolidation and quality optimisation	ESG integrated through exclusion lists, ESG expert opinions for critical cases, and greenwashing-prevention steps; ESG data collection is being initiated
Governance Architecture	Formalised governance arrangements for AI oversight and compliance (committees, specialised structures); emphasis on governance and risk oversight linked to regulation	Governance and reporting are more compliance- and transparency-oriented; sustainability claims not externally assured in the analysed sustainability report

Source: Author's own elaboration based on qualitative document analysis and cross-case comparison. Coding and thematic categorization were performed using ATLAS.ti.

In EU banks, the governance architecture appears formalized and multi-layered, integrating board oversight, specialized committees, and control functions to manage AI and ESG risks. NLB provides direct evidence that AI governance is institutionalized through a board committee that monitors AI compliance, AI accountability, and AI integration into operations. ING similarly links the increased use of AI to the need for risk governance and oversight, citing specialized structures such as the AI Risk Committee and the Center of Excellence to strengthen control and governance. These elements suggest that in the EU, governance aims to manage not only compliance, but also model risk and automated decision risk, creating a stronger foundation for deep AI–ESG integration.

In the case of Kosovo, governance appears more oriented towards compliance and transparency in reporting, with a clear emphasis on capacity building and voluntary reporting. Raiffeisen Bank Kosovo's sustainability report states that sustainability performance data and claims have not undergone external assurance by an independent party, indicating that the external verification and audit architecture is still immature at this stage. From an analytical perspective, this reinforces the interpretation that the emerging system operates with a more "compliance-based" governance, where internal policies, group rules, and ESG filters in financing are important, but where external assurance standards and the formalization of AI risk frameworks are less explicit in reporting.

4.8 Findings from process tracing: causal mechanisms

The process trace treats AI–ESG integration as a causal mechanism with five interconnected links: ESG data produces informative signals, which are processed through analytics and artificial intelligence, then translated into a risk assessment that conditions the financial decision, while the entire flow is overseen by the governance architecture. This approach makes it verifiable how reporting and digital capabilities are transformed into decision-making, as it seeks to identify the connections between the links and the points at which the institution intervenes.

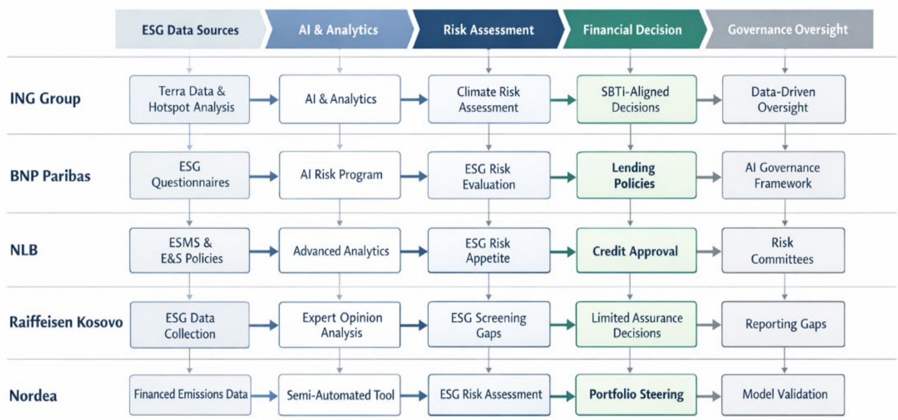

Figure 2: Process Tracing: Causal Mechanisms in AI – ESG Integration
Source: Author's elaboration based on qualitative document analysis and process tracing

In the case of European Union banks, the mechanism appears generally more institutionalized. ESG data is organized according to internal methodologies and standards, while analytics and digital tools serve as institutional intermediaries that standardize data interpretation and link it to risk. Risk assessment, especially climate risk and model risk, appears to be integrated into lending policies and portfolio management, enabling more traceable financial decisions at the process level. Governance oversight is an integral part of this chain because committees and control structures treat artificial intelligence and ESG as areas that require rules, accountability, and compliance, thereby strengthening the last link in the mechanism.

In the case of the emerging financial system, the mechanism is present, but often materializes through expert mediation and less automated processes. ESG data is in a consolidation phase, while analytics appears more as a capacity under construction than as an integrated layer in the basic risk models, while financial decisions rely on institutional filters such as exclusionary rules, reputational controls, and expert assessments for critical cases. Governance oversight is more oriented towards compliance and reporting transparency, which makes the mechanism functional for specific decisions, but less scalable at the full portfolio level.

Overall, tracing the process shows that the main difference between the EU and the emerging system lies not only in the presence of ESG or technology, but in the degree of institutionalization of the mediation between data and decision. In EU banks, the links are more closely connected through procedures, models, and committees; in the developing system, the links exist, but gaps appear more in the quality and coverage of data, in the formalization of analytics in risk assessment, and in the external verifiability of reporting.

4.9 Triangulation Analysis – Synthesis Method

The triangulated synthesis combines evidence from documentary analysis, cross-case comparison, and selective process tracing to develop analytically grounded interpretations of how ESG and artificial intelligence are integrated into banking decision-making. Figure 3 presents a synthesis of the triangulation of empirical findings, combining evidence from documentary analysis, cross-case comparison, and process tracing to draw analytical conclusions on the institutional mechanisms that influence the depth of AI and ESG integration in the banking sector.

The triangulated synthesis combines evidence from documentary analysis, cross-case comparison, and selective process tracing to develop analytically grounded interpretations of AI-ESG integration in banking decision-making. Figure 3 summarizes how ESG data, AI-enabled analytics, risk assessment, financial decision-making, and governance oversight are connected across the selected cases.

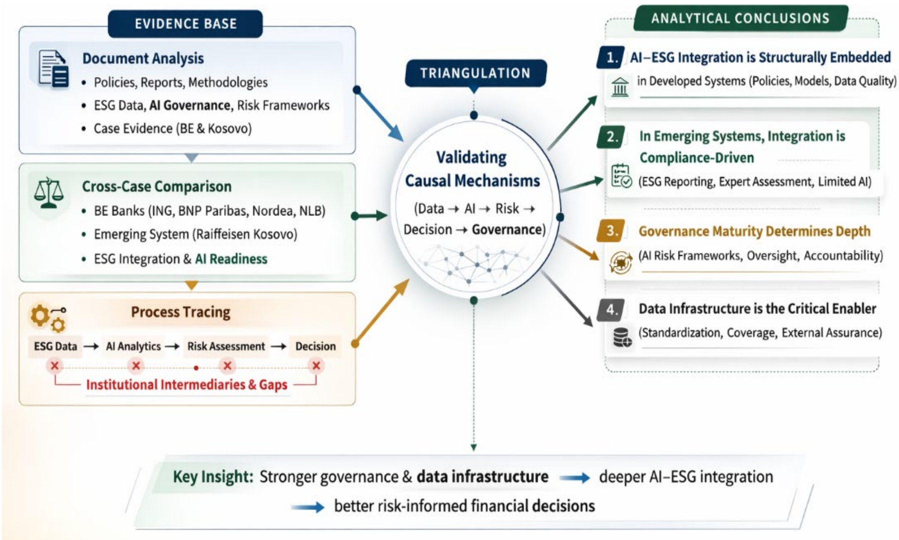

Figure 3: Triangulated synthesis of findings: AI – ESG integration in banking
Source: Author's elaboration based on qualitative document analysis, cross-case comparison, and process tracing of the selected banks

The triangulation suggests three main insights. First, in the EU cases, AI-ESG integration appears more structurally embedded in risk management and governance systems, supported by data-quality procedures, climate risk assessment tools, lending instruments, and committee-level oversight. Second, in the Kosovo case, integration appears more oriented toward compliance, ESG data development, exclusion mechanisms, and expert-based credit assessment, with more limited evidence of AI embedded in core decision-making models. Third, governance maturity is a key condition for deeper integration, as AI-enabled ESG decision-making depends on data quality, model risk controls, transparency mechanisms, and external assurance. Overall, the triangulated evidence suggests that the depth of AI-ESG integration depends less on the formal presence of ESG or AI and more on the institutional capacity to connect data, analytics, risk assessment, decision-making, and oversight.

5 Discussions

This study examined how artificial intelligence and advanced analytics are enabling the integration of environmental, social, and governance (ESG) factors into banking decision-making and the implications for sustainable governance in developed and developing financial systems. The discussion below structures the interpretation of the findings around the research questions, then presents practical implications, limitations, and directions for future research.

First, in relation to the research question on how AI enables ESG integration, the findings suggest that the key role of AI lies not only in automation but in the ability to turn ESG data into usable signals for risk management and decision-making. In banks with well-developed systems, ESG data tend to be processed in a standardized manner and integrated into the data architecture and internal controls, making the link between measurement, analytical interpretation, and use in key processes such as lending, monitoring, and exposure management more stable. This strengthens the argument that AI–ESG integration is a socio-technical transformation, in which technology has a real effect only when supported by institutional process design and data governance.

Secondly, regarding the research question on the impact of ESG on financial decision-making, the findings show that ESG is most operationalized when embedded in concrete decision-making instruments, such as lending policies, climate risk assessments, stress tests, and portfolio repositioning. In this context, ESG appears not only as a reporting framework but also as a criterion for capital allocation and for controlling exposures to transition and physical risks. In contexts with more limited capacity, ESG tends to be operationalized initially through protective filters, such as exclusion lists, reputational checks, and expert assessments, which influence the financial decision but make it more difficult to scale integration to the portfolio level.

Third, regarding the research question on governance and regulatory challenges, the study finds that governance maturity is a determinant of the depth of integration. In developed systems, AI and ESG governance tends to be formalized in dedicated structures, committee mandates, model risk controls, and transparency and compliance requirements. This reduces the likelihood that AI will be used opportunistically or solely for efficiency because it places the technology within a framework of accountability, audit, and control. In developing systems, governance appears more oriented towards compliance and reputational risk management, while the main challenge remains strengthening verifiability and increasing institutional capacity to manage model risk and to ensure transparency in decision-making assisted by analytics.

Fourth, in relation to the research question on the differences between the EU and the developing system, comparative analysis and process tracing show that the main difference is not simply the "presence of AI" or the "presence of ESG", but the way in which the links of the mechanism are connected from data to financial decision and supervision. In developed systems, the links tend to be more connected and institutionalized, making the mechanism more stable and traceable. In developing systems, the mechanism exists, but often relies on expert mediation and data consolidation phases, which produce gaps in standardization, analytical scalability, and verifiability.

The findings provide practical implications for both bank managers and policymakers, particularly when interpreted in light of the study's documentary and comparative design. For bank managers, the results suggest that AI–ESG integration should be treated as an institutional capability rather than only as a technological initiative. This requires standardizing ESG data, systematically documenting data quality, integrating ESG indicators into lending and portfolio processes, and developing clear AI governance mechanisms. Banks should strengthen model risk management, validation procedures, bias monitoring, transparency protocols, and internal audit mechanisms, especially where AI-supported tools influence credit assessment, risk classification, or capital allocation. In emerging financial systems, bank managers should prioritize consolidating ESG data infrastructure, staff training, developing internal ESG taxonomies, and gradually integrating ESG indicators into credit and risk management processes.

For policymakers and regulators, the findings indicate the need to develop clearer standards for ESG data comparability, AI transparency, model risk governance, and external assurance of sustainability-related disclosures. Regulatory frameworks should encourage banks to move beyond formal ESG reporting toward operational integration of ESG factors into risk management and financial decision-making. In emerging financial systems, particular attention should be given to institutional capacity-building, supervisory guidance, digital infrastructure, and minimum disclosure requirements for AI-supported financial decisions. Such measures would help reduce the risk of superficial compliance, strengthen accountability, and support a more credible transition toward sustainable and digitally enabled banking governance.

A key limitation of this study relates to its reliance on publicly available documentary sources, including annual reports, ESG reports, sustainability disclosures, risk management documents, and governance reports. Although these sources provide valuable evidence on how banks formally report, structure, and communicate AI–ESG integration, they do not allow direct observation of internal decision-making processes, model-level implementation, or managerial interpretations. As a result, the findings should be interpreted as analytically reconstructed patterns of reported institutional practices rather than as direct verification of operational AI use in lending, risk assessment, or portfolio allocation. This limitation is particularly relevant because banks may disclose AI and ESG practices selectively, depending on regulatory requirements, reputational considerations, and the level of transparency in public reporting. Therefore, the analysis may either underestimate actual internal practices that are not publicly disclosed or overestimate integration where strategic reporting is stronger than operational implementation. While methodological triangulation, cross-case comparison, and selective process tracing strengthen the analytical consistency of the study, further empirical validation would require access to internal bank documents, model validation reports, lending policies, risk committee materials, and interviews with risk, compliance, sustainability, and data analytics managers. Future research should therefore combine documentary analysis with primary qualitative evidence and, where possible, internal operational data to assess more precisely the depth, effectiveness, and governance quality of AI-enabled ESG integration in banking decision-making.

Future research could also test which governance configurations (committees, mandates, audit, and external assurance) are most effective at reducing model risk and increasing transparency in AI-assisted decision-making. Another important direction is to analyze the impact of data infrastructure quality and ESG indicator standardization on banks' ability to move from reporting compliance to operational and strategic integration.

6 Conclusions and Recommendations

This study suggests that AI-enabled ESG integration in banking decision-making should be understood not only as a technological development, but also as an institutional and governance process. The findings indicate that, in more developed financial systems, AI and ESG are more visibly embedded in risk management, lending, portfolio monitoring, and governance structures. In contrast, the case from an emerging financial system shows a more gradual form of integration, mainly focused on ESG data collection, reporting, compliance mechanisms, exclusion rules, and expert-based credit assessment.

The comparative analysis and selective process tracing provide evidence that the depth of AI–ESG integration depends on the institutional capacity to connect ESG data, AI-enabled analytics, risk assessment, financial decision-making, and governance oversight. When these links are supported by data-quality procedures, model risk controls, committee-level supervision, and transparency mechanisms, AI–ESG integration appears more traceable and operationally relevant. Where such mechanisms remain less developed, integration tends to be more fragmented and less scalable across core banking processes.

The study offers several recommendations. Banks in developed financial systems should further strengthen AI governance, model validation, bias monitoring, internal audit, and transparency protocols, particularly when AI-supported tools influence credit, risk, and portfolio decisions. Banks in emerging financial systems should prioritize developing ESG data infrastructure, standardized classification systems, staff training, external assurance, and the gradual incorporation of ESG indicators into lending and risk management processes. For regulators and policymakers, the priority should be to establish clearer standards for ESG data comparability, AI transparency, model risk governance, and sustainability disclosure assurance.

Overall, the study contributes to the literature on sustainable finance, digital transformation, and banking governance by showing that effective AI-ESG integration depends less on the formal adoption of AI or ESG reporting and more on the quality of institutional mechanisms that transform data into accountable financial decision-making. Future research should extend this analysis through interviews, internal banking documents, and model-level evidence to validate the operational depth of AI-enabled ESG integration across different financial systems.

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