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ARTIFICIAL INTELLIGENCE BASED GREEN CREDIT SCORING MODELS AND SUSTAINABLE LENDING DECISION IN THE KERALA BANKS.

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Abstract

The incorporation of the Artificial Intelligence (AI) in the banking credit-assessment systems is transforming the financial risk assessment and portfolio-management behavior (Davenport and Ronanki, 2018). At the same time, the increased regulatory and stakeholder emphasis on the Environmental, Social, and Governance (ESG) models is pushing lending policies in the direction of the sustainability-focused capital allocation (Fatemi and Fooladi, 2013; Friede et al., 2015). Although there is a growing application of AI-based credit-scoring methods, there is also still very little empirical data on how AI operationalises the ESG parameters to improve sustainable lending behaviour, especially in regional banking systems of the emerging economies.

The research question explored in the current paper is what the correlation between AI adoption is, ESG integration, and sustainable lending performance in banks service the Ernakulam district in Kerala. The quantitative, cross-sectional research design was used, where 150 banking professionals. The mediation analysis through regression was one of the methods that were employed to analysis the data using descriptive statistics, Pearson correlation analysis, multiple regression, and a regression-based mediation analysis.

The results indicate that the use of AI has a strong impact on the ESG integration and sustainable lending performance. The impact of incorporating ESG is positive and important regarding sustainable lending. The mediation analysis validates that the ESG integration is a mediating element between the use of AI and sustainable lending performance, which suggests that the technological capability is converted to sustainability results by a set of governance embedding mechanisms.

Keywords: Artificial Intelligence, ESG Integration, Green credit scoring, sustainable lending, sustainable Finance, Kerala Banking Sector.

1. Introduction

In the banking industry, the artificial intelligence (AI), machine learning, and predictive analytics in the credit risk assessment systems are fundamentally changing the industry (Brynjolfsson and McAfee, 2017; Davenport and Ronanki, 2018). Application The application of AI-based credit scoring to predict exercise better, minimize information asymmetry, and increase the efficiency of operations through the analysis of significant amounts of structured and unstructured data. These systems help financial institutions to get out of the traditional statistical modeling and get into dynamic and data-driven risk assessment processes.

Conventional measurement of credit risks is mainly based on the financial factors like income stability, repayment and collateral valuation. Although they are useful when screening the financial situation in the short term, their models tend to overlook the environmental and sustainability-related risks that express more in the stability of the long-term portfolio. Climate-related financial risks such as physical risks and transition risks are currently considered to be one of the major determinants of financial resilience (Bolton and Kacperczyk, 2021). Banks are therefore being pressurised to have sustainability parameters incorporated in the lending decisions.

1.1 Integrating ESG and Sustainable Finance.

ESG integration has become a theme of the sustainability of finance. The theory of Sustainable Finance assumes that ESG considerations would lead to greater long-term stability in a portfolio and lower the risk exposure to nature and regulatory risk (Fatemi and Fooladi, 2013). There is empirical evidence indicating that companies bearing high ESG performance have better financial results and less risk volatility (Eccles, Ioannou, and Serafeim, 2014; Friede et al., 2015).

The implementation of ESG in the banking environment entails the consideration of carbon exposure of borrowers, environmental conformability, transparency in governance and vulnerability to climate in the course of credit evaluation. This kind of integration will make sure that there is consistency in the financial risks management and sustainability goals. Nevertheless, the commercialisation of the ESG parameters in the AI-based credit rating models is under-researched.

1.2 AI -ESG Convergence- A Research Gap.

As much as adoption of AI increases the analytical potential, the transformation of technological sophistication to the sustainability outcomes is not automatically gained. AI technologies are only able to interpret the ESG data when these parameters are being deliberately implemented in credit decisions frameworks. In absence of designed ESG integration, AI can maximize the traditional financial measures without creating sustainable loaning results.

Current sources are more or less ignorant of the concept of AI adoption and ESG performance being different fields. The research studies on AI in banking are based on efficiency, profitability, and digital transformation (Bessen, 2019), whereas sustainable finance studies concentrate on ESG performance and climate risk mitigation (Weber, 2017). There is a scarcity of empirical studies that investigate the role of AI adoption on sustainable lending performance in terms of ESG integration, especially in the Kerala economic banking system which is undergoing development

1.3 Regional Environment Ernakulam District, Kerala.

The state of Kerala has a unique financial environment that is well-educated, massive penetration of digital banking services, and an increasing environmental consciousness. Energetic and involved in developing AI-based digital systems are its branches in Ernakulam district, one of the active commercial and financial centres, with branches of public sector, the private sector, and regional rural banks. Since Kerala is prone to climatic occurrences, like floods, it would be a smart idea to incorporate ESG parameters into the structure of credit evaluation.

Nevertheless, these context conditions cannot be considered the reasons to claim that empirical evidence of the relationship between AI adoption, ESG integration, and sustainable lending performance is few on a district level. The studies of the awareness or policy point of view involving the majority of the Indian studies do not test the structural relationship existing between technological capability, governance embedding, and the lending outcomes.

1.4 Research Purpose

As a response to this literature gap, the current study explores an answer to the question of whether the adoption of AI positively affects the sustainable lending performance or whether its effect works through ESG integration as a mediating governance process. The study is the best empirical test of the proposed relationships using the primary data as we examine the descriptive statistics, correlation analysis, multiple regression, and regression-based mediation analysis to test the speculations using the 150 banking professionals across the Ernakulam district.

This research introduces the digital transformation and sustainable finance lenses into a single empirical model, which makes it a valuable addition to the current developing discussion on climate-sensitive banking and provides details about the banking landscape of Kerala.

2. Literature Review

2.1 Credit risk assessment through Artificial Intelligence.

The artificial intelligence has significantly changed the nature of financial intermediation with the use of predictive analytics and through automating the complexity of credit assessment positions. Credit-scoring models developed using AI use machine-learning algorithms to process large datasets and identify non-linear relationships that the conventional statistical models easily ignore (Bessen, 2019; Brynjolfsson and McAfee, 2017). As argued by Davenport and Ronanki (2018), AI has a beneficial effect on operations efficiency and decision quality because it reduces the issue of information asymmetry and reinforces predictive risk profiling.

Recent empirical studies prove that AI-underwriting largely outperform traditional logistic regression models of default risk prediction and improving more the quality of loan portfolios (Lessmann et al., 2015). Furthermore, machine-based credit rating enhances the scalability and eliminates human bias during lending processes (Jagtiani and Lemieux, 2019). However, most studies on AI in banking are based on the empirical data focused on efficiency, reduction in costs, and profitability as opposed to sustainability outcomes.

Although AI has the potential to utilize alternative and multidimensional sources of data, such as those of environmental indicators, the current body of literature provides factual evidence on the integration of ESG metrics into credit-scoring systems through AI. This fact gap highlights the need to study, whether technological competence translates into lending performance in the manner of sustainability.

2.2 ESG and sustainable Finance Integration.

Sustainable finance insists on the integration of environmental and social concerns in the economy decision making and therefore, the stability of the economy in the long run (Fatemi & Fooladi, 2013). ESG integration is a convened process of incorporating the criteria of the environment, societal level, and administration in investment and lending decisions (Friede et al., 2015).

The overwhelming evidence of empirical research indicates a positive correlation between the ESG performance and financial performance. Eccles et al. (2014) discover that high-sustainability companies perform better in long-term stock-market than low-sustainability ones. Friede et al. (2015) meta-analysis indicates that about 90 percent of studies establish the non-negative correlation among ESG and corporate financial performance.

Weber (2017) proposes in the banking industry that ESG integration will minimise the reputational risk and increase risk-adjusted returns. Likewise, Scholtens (2006) points out the contribution of the financial institutions that direct capital flows to the activities that environmental conservation. Banking institutions with strengthened ESG standards in lending products are in a better situation to handle climate-based financial risks and regulatory or risk exposure.

Nevertheless, even though there is a extensive literature on ESG integration in the context of investment portfolios, little literature plans to examine its implementation in the context of AI -based credit-scoring tools. There is a lack of study on the extent of interaction between digital innovation and ESG governance.

2.3 Climate Risk and Financial Stability.

Climate change also creates both physical (housing damages caused by extreme weather) and transition risks (change in policy and market concerns toward decarbonization), causing a major impact on financial institutions (Bolton & Kacperczyk, 2021).

Similarly, the reserve bank of India (2023) puts an importance on introducing climate related financial risk in Indian banking systems.

Regions prone to floods like Kerala and other areas prone to climate related disruption like floods, the environmental risk is very relevant to consider during credit assessment. Lack of consideration of environmental vulnerability can result in under-observation of the probability of default in the long-term.

Although more people have recognized and become aware of climate risk, the empirical studies that could help to explain how the systems supported by AI can operationalize climate-sensitive risk measurement in banking ecosystems in regions are rather rare.

2.4 Technology Adoption and institutional integration.

Davis (1989) developed the Technology Acceptance Model (TAM) that underpins the process of organizational adoption of technology because of organizational perceived usefulness and ease of use. The use of AI in banking institutions is contingent on the perception by the managers that digital systems can improve the accuracy of decisions made by the organization and efficiency of services provided (Venkatesh et al., 2003).

The research on digital transformation shows that the adoption of technology is not sufficient to strategically improve a performance unless applied to organizational processes (Bharadwaj et al., 2013). As a result, it is critical to ensure that AI implementation reflects governance systems to bring sustainability results.

A further view based on this aspect of integration is the Stakeholder Theory (Freeman, 1984) which submits that financial institutions ought to consider more broad stakeholder interests e.g. environmental and societal effects in strategic decision making.

2.5 Integrated Perspective: AI, ESG, and Sustainable Lending.

Even though previous research efforts consider the adoption of AI and ESG performance on a case-by-case basis, there is little research on the combination of the two constructs in a single, empirical setting. According to the Sustainable Finance Theory, the introduction of the ESG criteria increases the stability of a portfolio in the long term (Fatemi and Fooladi, 2013), whereas AI supplements the analytic capability (Davenport and Ronanki, 2018). Nonetheless, the sustainability results will be achieved only when ESG parameters are implemented into digital credits systems in an orderly manner.

According to the mediation logic, the use of AI will reinforce the ability of ESG integration, which subsequently leads to the conclusion that sustainable lending will be improved. This is a view that goes beyond efficiency-based discourse and the argument that ESG integration constitutes a governance that can convert technology capability into sustainability results.

There are a small number of empirical studies that can confirm this mediation mechanism, especially in the new regional banking ecosystems like Kerala. Thus, the current research fills in the gap in research by conducting a regression-mediation model to establish the relationship among AI adoption and ESG integration as well as sustainable lending performance.

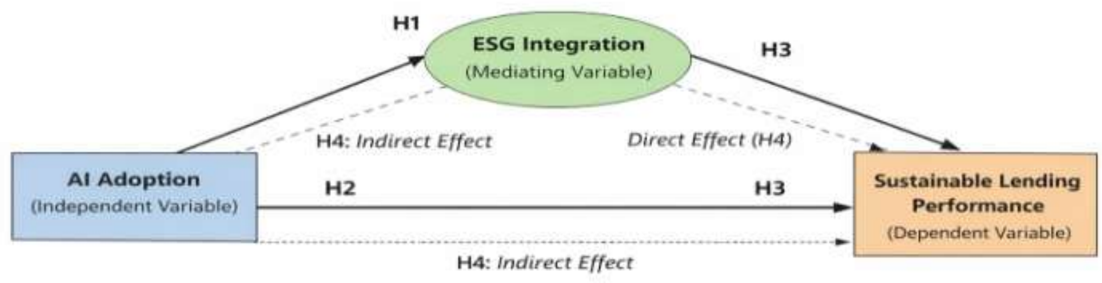
3. Objectives of the Study

- To examine the relationship between AI adoption and ESG integration in the credit risk assessment systems of banks in Ernakulam district.
- To analyse the impact of AI adoption and ESG integration on sustainable lending performance.
- To evaluate whether ESG integration mediates the relationship between AI adoption and sustainable lending performance.

Conceptual Model and Hypotheses.
Conceptual Framework

This paper suggests a regression-based mediation model to test the inter-relations between Artificial Intelligence (AI) adoption, Environmental, Social, and Governance inclusion, and sustainable lending performance amid the banks in the Ernakulam district located in Kerala.
The conceptual model explores the following:

- The immediate impact of the adoption of AI on the integration of ESG.
- The direct impact of the adoption of AI on sustainable lending performance.
- The immediate effect of the ESG integration on sustainable lending performance.



- The hidden impact on sustainable lending performance by adoption of AI via integration of ESG.

In contrast to the traditional models of credit risk, those which are based on the AI-powered credit scoring algorithms allow banks to incorporate the data which has more than one dimension, including the variables related to the environment and sustainability. However, the implementation of technological capability into sustainability-focused lending results depends on the systematic introduction of ESG parameters in credit evaluation procedures.

Based on this, the model has three constructs.

- The independent variable is the adoption of AI.
- It comprises the integration of ESG (Mediating Variable).
- Sustainable Lending Performance (Dependent Variable)

The inter-construct interrelations are assessed with the help of a pearson correlation, simple regression, multiple regression and regression-based mediation.

AI Adoption

AI adoption is defined as the degree to which banks utilize the artificial intelligence technologies in credit decision-making processes, which could be machine learning algorithms, predictive analytics, underwriting systems (which are automated) and risk-scoring models based on data.

Artificial intelligence increases predictive precision, decreases information asymmetry and efficiency in assessing risks (Davenport and Ronanki, 2018). The Technology Acceptance Model (Davis, 1989) argues that the institutions embrace technology when they are deemed to increase efficiency in operations as well as the quality of decisions made. In the banking business, AI increases the levels of analytical ability and enables the handling of sophisticated sustainability signatures in risk-assessment tools.
Therefore, the adoption of AI will affect both ESG integration and sustainable lending performance in a positive way.

Hypotheses:
H1: The use of AI has a positive impact on the integration of ESG.
H2: The adoption of AI has a positive impact on sustainable lending performance.
The simple regression analysis is applied to these propositions.

ESG Integration

ESG integration refers to the systematic inclusion of the Environmental, Social, and Governance factors in the lending decision and credit-risk assessment. This includes testing of the carbon exposure of the borrower, environmental integrity, governance disclosure, and climate vulnerability.
The Sustainable Finance Theory assumes that integration of ESG parameters would contribute to stability in the long-term portfolio and reduce climate risk financial challenges (Fatemi & Fooladi, 2013). ESG integration enhances the risk differentiation by taking into consideration environmental and regulatory risk exposures that are not reflected by conventional financial factors.
In this context, the ESG integration can be seen as a governance tool which connects the technological capability with the results of the sustainability-focused lending.

Hypothesis:
H3: ESG integration has a positive effect on sustainable lending performance.
Regression analysis is used in investigating this relationship.

ESG Integration ESG Mediation Effect.

In addition to the direct relationships, this research study examines the proposed idea of ESG integration mediating the relationship between sustainable lending performance and AI adoption.
The theoretical explanation is that AI gives the technological support needed to handle sustainability-related information. Yet, the success of sustainability is achieved only in the case when ESG parameters have been intentionally integrated into the AI-based credit systems. Therefore, the ESG integration can serve the role of a transmission channel where the adoption of AI can impact sustainable lending performance.
Regression mediated analysis sets up mediation that exists when:
1. ESG integration is strongly related to the adoption of AI.
2. The use of AI is an important predictor of sustainable lending performance.
3. Sustainable lending performance is largely anticipated by ESG integration.
4. The introduction of ESG integration in the regression model reduces the coefficient of AI adoption on the sustainable lending performance.
In case the direct effect is significant but is reduced, one ascertained partial mediation.

Hypothesis:

H4: ESG integration ranks in-between AI adoption and sustainable lending performance.

Further developing the arguments of the theoretical rationale and empirical research approach, a partial mediation is expected, that is, the adoption of AI has a direct and indirect positive effect on the sustainable lending performance based on the inclusion of ESG in the processes.

4. Research Methodology

The research study has a quantitative, cross-sectional, explanatory research design to examine the structural interrelations between artificial intelligence (AI) adoption and environmental, social, governance (ESG) integration and sustainable lending performance in banks located in Ernakulam district, Kerala. Quantitative methodology was chosen because the proposed hypothesized relationships are to be tested empirically through the use of a statistical method. The information was collected at one time period within a three-month period that allowed measuring the

modern state of AI-based credit scoring application and ESG integration to a lending system. The conceptual framework is regression based and it entails Pearson correlation, simple regression, multiple regression, and mediation analysis.
The Ernakulam district has been selected as the study area because of its intense banking penetration, well-developed digital infrastructure and the flourishing interest in sustainable finance. The district covers the following, public, private and regional rural banks enduring with digital transformation programs.
The research sample included banking practitioners in charge of credit evaluation, risk analysis and digital banking practices and ESG regulations. The purposive sampling was used to offer 150 respondents to obtain domain-specific knowledge applicable to AI credit scoring and sustainability integration.
The structured questionnaire that included 24 Likert-scale questions was used as a primary source of information to gather primary data dedicated to measuring AI adoption, ESG integration, and sustainable lending performance. The institutional visits, formal communications, and professional networks were used to conduct data collection. Theoretical and conceptual development was based on secondary data, which was based on peer-reviewed literature, regulatory reports and academic databases.

5. Analysis and Results

5.1 Descriptive Statistics

Variable	Mean	SD
AI Adoption	3.84	0.62
ESG Integration	3.71	0.58
Sustainable Lending	3.76	0.65

Interpretation

The descriptive statistics indicate moderate-to-high rates of AI adoption and sustainability integration among banks which are situated on the district of Ernakulam. The descriptive statistics of the AI Adoption (M= 3.84) shows that Banks have significantly applied AI-based credit-scoring systems, such as predictive analytics and automated underwriting, to the process of lending.
The ESG Integration mean value (M = 3.71) shows that the environmental and governance parameters are being incorporated moderately in credit-risk assortment designs, yet total institutionalization of this service has not occurred yet.
The Sustainable Lending Performance (M =3.76) is a relatively good fit between technological modernization and the environmental responsible lending activities.
The minimal standard deviation values: they are all less than 1.0 ensure high response consistency and low variability in the responses of the participants hence justifying the reliability of the measurements.

5.2 Correlation Analysis

Variable	AI	ESG	Lending
AI	1		
ESG	0.702**	1	
Lending	0.716**	0.744**	1

All correlations significant at p < 0.01

Interpretation

Pearson correlation coefficients, all constructs show strong and statistically importantly positive relationships.

- ESG Integration is positively associated with AI Adoption ($r = 0.702$, $p < 0.01$) and implies that the more significant AI adoption by the bank, the more it becomes more embedded in credit decisions.
- Sustainable Lending Performance is also highly correlated with the AI Adoption ($r = 0.716$, $p < 0.01$), which implies that the technological development is linked to the sustainability-congruent lending performance..
- ESG Integration has shown a correlation with Sustainable Lending ($r = 0.744$, $p < 0.01$), which hints at the fact that the governance mechanisms have the strongest impact on the sustainability performance.

All the correlations are significant and substantial, thus, preliminary conditions to test regression and mediation are met.

5.3 Regression Analysis

To test H1, H2, and H3, linear regression analysis was conducted. The results are summarized below.

Summary of Regression Results

Hypothesis	Path	β	p-value	Result
H1	AI → ESG	0.702	.000	Supported
H2	AI → Lending	0.716	.000	Supported
H3	ESG → Lending	0.744	.000	Supported

Model Fit:

- R^2 (ESG) = 0.493
- R^2 (Lending – direct AI model) = 0.512

Interpretation

The regression results confirm that AI adoption significantly predicts ESG integration ($\beta = 0.702$, $p < 0.001$), explaining 49.3% of the variance. This indicates that nearly half of the variation in ESG embedding within credit systems can be attributed to technological adoption.
AI adoption also exerts a strong positive effect on sustainable lending performance ($\beta = 0.716$, $p < 0.001$), accounting for 51.2% of the variance. This demonstrates that AI-driven credit scoring directly enhances sustainability-oriented lending practices.
Further, ESG integration significantly influences sustainable lending performance ($\beta = 0.744$, $p < 0.001$). The higher beta coefficient suggests that governance embedding is a stronger predictor of sustainable lending than technological capability alone.
All regression coefficients are statistically significant ($p < 0.05$), thereby supporting H1, H2, and H3.

5.4 Mediation Analysis

To test H4, ESG integration was introduced as a mediator in the relationship between AI adoption and sustainable lending performance.

Mediation Results

Mediating Relationship	**Indirect Effect**	**Significance**	**Mediation Type**
AI → ESG → Lending	0.307	$p < 0.001$	Partial

After including ESG integration in the regression model:

- AI β reduces from 0.716 to 0.421
- ESG $\beta = 0.467$ ($p < 0.001$)
- R^2 increases from 0.512 to 0.590

Interpretation

- The fact that the standardized coefficient of AI adoption decreased by 0.716 to 0.421 after the implementation of ESG integration poses a reason to believe that the effect of AI on sustainable lending acts indirectly through the implementation of ESG integration.
- The indirect effect of 0.307 is statistically significant ($p<.001$) which validates that mediation is present and the direct effect of AI is significant even after considering the integration of ESG therefore mediation is partial, and not complete.
- R^2 has increased between $R^2 = 0.512$ to $R^2 = 0.590$, which allows to conclude that ESG integration contributes to the predictive value of the model, which means that a sustainable lending performance is not enhanced only by the technological progress but by the agreement in the governance as well.

Thus, hypothesis H4 is confirmed, which states that ESG integration interposes the connection between AI adoption and sustainable lending performance in part.

6. Findings and Discussion

This part will outline the significant results of the research and comment on them according to hypotheses introduced in the work and the available literature.

6.1 AI Adoption and ESG Integration.

The regression analysis confirms that the adoption of AI has a significant impact on ESG integration ($b = 0.702$, $p < 0.001$), which accounts for 49.3% of the variance in the ESG integration. This implies that the technological capability contributes significantly to the process of embedding governance in credit decision systems.

The result indicates that financial institutions which rely on AI-based credit evaluation models have more chances of incorporating environmental and governance factors in their lending models. AI facilitates analytical prowess, enabling organizations to handle complicated data, such as sustainability metrics, including carbon exposure, regulatory adherence, and risk exposure of climate.

This finding aligns with the Technology Acceptance Model (Davis, 1989) that provides that perceived usefulness is what influences adoption of technology. In this regard, AI implementation contributes to improving operational efficiency and increasing the institutional capacity to integrate ESG metrics.

The result is also applicable to the previous literature (Davenport and Ronanki, 2018) as it proves that the implementation of AI can also bring about efficiency improvements, as well as change the way banking institutions are governed. In this way, H1 gets empirical support.

6.2 AI adoption and sustainable lending performance.

The paper concludes that the adoption of AI has a significant effect on sustainable lending performance ($b = 0.716$, $p < 0.001$), which accounts for 51.2% of the variation. This shows that technological modernization would play a direct positive role on sustainability-informed lending practices.

Artificial intelligence credit products enhance better risk differentiation, vulnerability of a borrower, and portfolio management. Such functions allow banks to match the lending policy with the long-term risk management policies, such as climate risk assessment.

The research is consistent with previous studies that have focused on the effectiveness and forecasting capability of AI-based credit scoring systems (Lessmann et al., 2015). Nonetheless, the current research fills the gap in literature since it shows that AI does not influence financial performance alone but results in sustainability as well.

These findings indicate that digital transformation by itself has a direct impact that is strong on sustainable lending performance and as such, H2 is proved.

6.3 ESG Integration and Sustainable Lending Performance

It is found that the direct influence of ESG integration is the most significant on sustainable lending performance ($b = 0.744$, $p < 0.001$), and it explains 55.3 percent of the variation. It means that the governance embedding is a stronger prognosticator of sustainability results in comparison with technological ability.

The integration of ESG guarantees that the parameters of sustainability are integrated into the lending systems in systematic ways, which affect the decision to provide credit. This result is a strong indicator of Sustainable Finance Theory (Fatemi and Fooladi, 2013), which states the need to use environmental and governance standards to increase the long-term stability of a portfolio.

The relatively greater coefficient of beta about the integration of the ESG over the adoption of AI indicates that the governance orientation is a more proximal predictor of sustainable lending outcomes. Although AI supports better analytical infrastructure, ESG incorporation is a strategic way of maintaining sustainability.

Therefore, H3 is supported.

6.4 ESG Integration and Mediation.

The mediation test proves that the association between the use of AI and sustainable lending performance has a partial mediation by ESG integration. In the event of incorporating ESG integration into the regression model:

- The beta of AI adoption is lowered to 0.421.
- The importance of ESG integration is still high ($b = 0.467$, $p < 0.001$).
- The explanatory power goes up to R2 = 0.512 to R2 = 0.590.
- The indirect effect (0.307) is statistically significant ($p < 0.001$).
- These outcomes attest to partial mediation.

The results show that the adoption of AI has two channels in impacting sustainable lending performance:

- Direct technological direction - improving the efficiency of the analysis and accuracy of the decision.
- Indirect pathway of governance - reinforcement of ESG integration, which in turn, introduces sustainable lending.

This two-way flow mechanism indicates the structural legality of ESG incorporation as a transmission channel between technological ability and sustainability results.

The findings bring into the focus of the previous literature the fact that digital transformation should be combined with governance embedding to attain significant sustainability performance. Technology cannot fully work without being in line with the ESG frameworks. Thus, H4 is supported.

6.5 Integrated Discussion

The outcomes show that: The use of AI will increase the capacity to integrate ESG. ESG integration is at the centre of establishing sustainable lending results. The technological development is a contributor in both direct and indirect ways to the sustainability performance.

The mediated model justifies 59% of the sustainable lending performance variances, which shows a strong predictive validity. Regionally speaking, the results offer empirical data on the Ernakulam district level, indicating that the digital innovation to sustainable finance ambition can successfully be aligned on the level of district-based banking ecosystems.

The research has three contributions to the current literature:

- It incorporates the adoption of AI and ESG governance into one concrete empirical framework.
- It confirms mediation-based model through regression analysis.
- It presents evidence within the banking sector of Kerala on a region basis.

All in all, the results point to the fact that technology only does not influence sustainable lending performance but the strategic combination of technology and ESG governance mechanisms.

7. Conclusion

This study was attempting to investigate the structural connection of artificial intelligence (AI) adoption, Environmental, Social and Governance (ESG) integration, and sustainable lending performance among Pakistani banks located in Ernakulam district in Kerala. Using regression and mediation analysis shows that the research considered direct and indirect routes on which digital transformation presents an impact on sustainability-oriented lending outcomes.

These findings suggest that AI implementation has a strong positive impact on ESG integration and can observe a direct positive effect on sustainable lending performance. However, ESG integration turned out to be the most effective forecast of sustainable lending results, and it highlights the idea that the impact of governance embedding is more proximal than in the case of technological capability. The mediation analysis also shows that the effect of AI adoption of sustainable lending performance is mediated by ESG integration, in part. The above findings suggest that AI-based credit scoring enhances the efficiency of analytics and risk profiling, but this effect of the approach is even more significant when the ESG parameters are incorporated into credit decision-making frameworks systematically. The paper therefore provides an important critical point that questions further technological modernization alone would not be enough to achieve sustainable finance goals. The ESG integration plays the role of the operational mechanism, which renders digital capability into climate-consistent lending practices. Therefore, the concept of sustainable banking does not simply emerge as the coincidence of digital innovation, but as the manifestation of hegemony between AI infrastructure and the system of governance.

Providing district-level empirical information about a regional banking ecosystem in India, the study contributes to the growing literature on sustainable finance and indicates the necessity of balancing the technological change with ESG governance in order to deliver sustainable meaningful results.

8. Policy Implications

The research findings of this paper have a few relevant policy conclusions, which include banking institutions, regulators, and financial policy makers in Kerala and other similar regional banking institutions.

8.1 The implication of the study at an institutional level.

To begin with, through the adoption of AI, there is a strong improvement in the ESG integration and sustainable lending performance. In turn, banks cannot just surrender to simple digital transformation and invest strategically in the AI that will be able to handle the data that are related to sustainability. AI-based models of credit scoring should be restructured, so that they also follow the ESG scorecard, including carbon exposure, environmental compliance, presence of transparent governance, and vulnerability to climate risks.

Second, since it was found that the ESG integration was the strongest indicator of sustainable lending performance, financial institutions should institutionalize ESG systems on the credit appraisal policy. The inclusion of ESG should cease to be a reporting or compliance exercise, but rather, it must be incorporated directly as a part of the loan sanctioning requirements, risk rating systems, and in portfolio monitoring systems.

Thirdly the partial mediation effect suggests that technological capability cannot be sufficient working alone. Banks ought to create in-house ESG governance boards, sustainability-risk boards, and cross-functional liaisons between the digital banking and compliance departments to make sure that AI systems are aligned to the sustainability goals.

8.2 The Implications or the Regulatory and Policy-Level.

Regulatory wise, the financial regulators including the Reserve Bank of India and state banking regulatory bodies could look at coming up with standardized ESG-based credit- risk assessment policies. Sponsoring standard ESG-scoring systems across the banks may improve comparability and decrease the asymmetry in the informing the sustainability-reporting.

Moreover, the regulatory incentives, such as the priority lending, capital forbearance policies, attachment of the green-finance tax, etc., can be used to motivate banks to embed ESG into AI-based systems more strongly.

Due to the vulnerability of the climate in Kerala, the policymakers also could encourage climate-fine credit-assessment models to reduce the exposure to the financial risks on a long-term basis in flood prone and environmentally pricier regions.

8.3 Alignment of Digital Governance and Sustainable Finance.

The research predicts the significance of combining the digital transformation strategies and the sustainable finance goals. Banks must not consider the use of AI and compliance with ESG a different strategic effort. They ought, instead, to strive towards combined digital governance whereby AI infrastructure and ESG structures work in a synergistic manner.

Banking professionals should also be trained on ESG analytics, climate risk modelling and AI-based sustainability assessment, which can also strengthen institutional capacity.

The policy implication, in general, is unanimous, namely, sustainable lending performance is enhanced when the technological innovation is structurally adequate according to the rules of governance of environmental sustainability.

9. Future Research Directions

Even though the current research provides abundant empirical information, there are still a few potential research lines.

9.1 Geographic Expansion

The current investigation will be limited to the Ernakulam district. The potential scholarship ought to extend its objectives to a greater area by covering other districts in Kerala or carry out inter-state comparisons across India so as to maximize the generalizability of the study. Further details on the trend of digital transformation and integration of sustainability can be provided by means of comparative studies comparing the characteristics of urban, and rural banking ecosystems.

9.2 Longitudinal Studies

The cross-sectional design is used in the ongoing study. The future studies can use longitudinal data gathering to determine the effect of AI adoption and ESG integration on sustainable lending performance over time thus the dynamic change of digital maturity and governance embedding.

9.3 Higher-order Methods of Analysis.

Although this research employed regression-mediation analysis, researchers in future studies can adopt Structural Equation Modeling (SEM), panel regression of data, or multilevel regression advocacy to reduce the underlying causal and hierarchical relationship and influence on the desired outcome.

9.4 Additional Variables

The moderating or mediating variables that may be included in future studies include:

- Organizational culture
- Regulatory pressure

• Climate risk exposure
• Digital maturity levels
Financial performance indicators.

These variables could enable a better understanding of the results of the influence of institutional and environmental factors on sustainable lending.

Borrower level is another perspective that is subject to change based on the loan amount sought by the borrower and the lender's views on the borrower's ability to repay the loan within the agreed time period specified in the loan contract (9.5).

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