# Can Artificial Intelligence–Driven Green Banking Accelerate the Circular Bioeconomy in Sustainable Agriculture?: A econometric model approach

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**Abstract.** Recent empirical evidence highlights the importance of artificial intelligence–driven green banking to mitigate against the high environmental degradation to agricultural productivity in developing economies. This paper analyses the relationship between artificial intelligence–driven banking services and sustainable agricultural performance with green finance's institutional framework using propensity score matching. This paper devotes the empirical attempt to understanding the interaction between different dimensions of the banking sector and rapidly growing circular bioeconomy activities at different stages of development. The level of heterogeneity between the two types of agricultural producers is determined using analytic hierarchy process and estimations show that digitally supported farms have lower operational risks than traditional farms. Using panel econometric techniques, we have gained valuable insights into the continuous evolution of interactions between financial institutions, agri-tech firms and circular bioeconomy initiatives at different development stages for reaping the benefits of sustainable finance systems in particular and keeping environmental resilience at acceptable levels. After controlling all the structural and macroeconomic variables, the results show that green credit allocation and digital banking penetration are positively related for the overall agricultural output and negatively related for carbon intensity which confirms that inherent difference between technological capabilities among these two farming system types. Overall, in the context of sustainable agriculture, the results provide strong evidence in favor of policy coordination where higher financial inclusion with fierce competition from fintech institutions and its innovation networks reduce environmental externalities.

**Keywords:** Artificial intelligence–driven banking, green finance, sustainable agriculture, circular bioeconomy, propensity score matching.

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# 1. Introduction

The rapid development of artificial intelligence in digital banking systems has contributed to create highly integrated financial platforms such as green credit scoring and smart lending systems that are core items which have often failed to support sustainable agricultural transformation effectively. Recent studies analyze the interaction between artificial intelligence (and its digital infrastructure) and total agricultural productivity, using a panel dataset and econometric modelling, for the period of 2012–2023, on a cross-country basis [1,2,3]. From a theoretical point of view, these developments would not have occurred in an inefficient financial system because one of the major foundations of these technological transitions is financial inclusion under institutional stability [4,5].

Underlying the varying outcomes are two conditions for the effective interaction between financial technology and sustainable agriculture: (i) increased spending on digital infrastructure and human capital, and (ii) to the extent that additional investment requires resources outside the agricultural sector, it should not be at the expense of environmental protection and rural development. However, in real life situations, farming enterprises do not utilize these advanced financial tools, instead they make use of traditional credit mechanisms such as informal lending [6]. Nevertheless, existence of conflicting and fragmented evidence on this issue produced mixed and inconsistent results [7,8].

Due to structural limitations of financial markets arising from strong regional disparities in income and infrastructure quality, rural producers are also exposed to severe financial constraints and market uncertainties that are difficult to overcome especially because smallholders are not considered credit-worthy. Additionally, the inconsistent results in the empirical literature make difficult to know whether coordination of green finance policy and effective cooperation between financial institutions in the agricultural sector could serve an efficient means of improving farm productivity [5,6,7,8,9,10]. Think tanks and researchers of sustainable finance have struggled to address these issues through empirical modelling approaches [7,8,9,11,12]. There are ample evidence in the existing literature which shows that digital financial inclusion is more effective in the regions where institutions are strong and have less information asymmetry.

In addition, Ferreira and Costa examined the impact of artificial intelligence on total output in the period between 2010 and 2023, using vector autoregression models, which revealed a significant causal relationship of digital finance on the bioeconomy in the long run. Although studies conducted by Ahmed or Khan focused on the effects of green banking between financial institutions and agricultural enterprises; but these studies did not cover any interaction between artificial intelligence and eco-friendly practices among farming systems.

Traditional regression model provided little evidence in favor of policy makers and bank managers regarding managerial and technological skills. Even though there are some of the comparative studies comparing the productivity gap between digital farms and their conventional counterparts, those studies did not put much focus on how artificial intelligence may impact risk-sharing among agricultural producers. Existing literature has given limited attention towards digital banking platforms and their impact on circular production systems [13,14]. As per the authors' best knowledge, there is no comprehensive empirical study on how the variable artificial intelligence can impact their performance in different institutional contexts. Moreover, the aim of this paper is to examine the relationship between artificial intelligence–driven banking and sustainable agriculture in the circular bioeconomy, as well as to analyze the response of agricultural enterprises to different levels of digital financial services.

This study adds to the literature by investigating the interaction of different financial actors in developing economies, the only group in the world with a high dependence on agriculture and the largest population engaged in farming activities, totalling millions in rural areas.

The findings of the study are crucial for policymakers to address the emerging issues whether it is related to financial inclusion or technological adoption which are essential for the development of the green finance system. Findings are also important to regulators and practitioners, including the policy frameworks recently introduced by the government, as it provides guidance on digital investment and environmental governance. For that reason, unlike other approaches in agricultural finance research, the adopted framework consists of building multiple structural equations, in order to take into account all different channels through which main financial innovations can affect the farming sector [15].

This study has shown that its novel contribution produced by the integration of artificial intelligence–driven green banking using the digital–green synergy approach was much better ([6]; [9]) because multi-dimensional interactions in circular bioeconomy and sustainable agriculture was explicitly modeled ([7]). Our study also has shown that more than majority of the existing studies in the green finance and digital banking literature maintained the single-channel mode of delivery, i.e., by using conventional regression approaches where they explained the financial–agriculture linkage while artificial intelligence passively remained excluded and limited attention took place.

A "digital-green synergy" proposed by this recent model indicates more investment in artificial intelligence and green finance could enhance the efficiency of the agricultural system by lowering farmers' financial vulnerability over the long run. Further, the interaction between the adoption of technology in the banking sector and the agricultural economy has been systematically examined. The model is founded on the study and comparison of both traditional and digital financial systems which is different from the conventional view which only analyzes the credit market.

## 2. Methods

Primary survey data are collected from the agricultural and banking sectors from 2012 to 2023 in the selected developing economies of Asia and Africa. Secondary data has been taken from the World Bank Development Indicators and FAOSTAT databases over the period 2012–2023. We employed a stratified random sample of agricultural enterprises and commercial banks of selected countries through national statistical offices. The sample for this research includes a number of farming enterprises and financial institutions from both sectors; rural producers in the agricultural sector and commercial banks in the financial sector.

The researcher's role in this study was as an integrated methodological observer. This means that the researcher observed how the models combined PSM, GMM and AHP procedures before and after estimation, and how the data participated in the estimation process itself.

In addition, in order to establish the sequential structure of the framework used, the data were transformed to a unified model using integrated PSM-GMM-AHP procedures. In the final stage, a post estimation was conducted to examine whether the variables have applied the combined strategies in their relationships, followed by an evaluation of its consistency. The analysis served to demonstrate that the model developed by the researchers fit the data collected.

The variables representing digital finance adoption, green credit allocation, agricultural productivity and carbon intensity are measured by composite indices, ratios, growth rates and logarithmic values. The number of observations for farming enterprises is 4,860 and for banking institutions is 1,240. The sample size indicates over 70 percent of agricultural producers are located in the rural areas of developing Asia and Africa (smallholders and medium-scale farms).

The sample size clarification was explicitly stated, which exceeded the recommended cutoff value of minimum required observations for panel consistency. Stratified random sampling was applied in this study [13]. [13] claimed that the sample can be reduced and matched for a variety of reasons such as the availability of balanced treated–control observations being familiar to the estimation procedure and more importantly, the sample serves the purposes of the propensity score matching analysis.

These countries are chosen as the sample in this study because due to the fact that these economies especially Uzbekistan, Indonesia, Vietnam, Nigeria, Ethiopia (refer as developing agrarian economies) together with Bangladesh hold more than 60 percent of agricultural employment in the world ([1]). Data for variable artificial intelligence adoption and green credit was obtained from discussions in annual banking reports. According to the existing literature, a number of other control variables could have been included for this analysis. However, these variables might not be fully observable, since our empirical model captures well the main transmission channels through which financial innovation can influence the farming sector.

Given the consideration of both theoretical and empirical evidence above, this study uses the propensity score matching approach to estimate the causal relationship between digital banking and farm performance by basing on the framework proposed by ([2]; [3]; [4]; [5]). The continuous propensity score matching (PSM) logit-based estimation approach, otherwise logistic regression, such that it estimates the conditional probability of treatment as a function of observed covariates. To estimate the propensity score, a logit model will be first estimated by maximum likelihood, robust standard errors and bootstrapping procedures ([2]; [5]).

The estimation and matching procedure of the sample was performed by statistical software in the form of STATA and R. Propensity score matching has an advantage against ordinary least squares or fixed effects where the treatment is not a continuous measure of exposure and can be evaluated at each point of distribution ([4]; [6]). After matching observations, the number of treated units was reduced to balanced pairs. The comparison of the mean outcomes of treated units with respect to the matched control group is conducted using the matching estimator in equation (1).

We controlled for the observations having a standardized mean difference greater than 0.1, reducing the matching bias to minimum levels. As defined by, bias is an "opposite measure of balance where a high bias implies lower matching quality" ([5]). The treatment indicator variable takes the value of one if the farm uses digital banking as its main financial channel and zero if otherwise. The values close to zero indicate good matching quality, while the values close to one are signs of a weak balance condition. The matching statistics are beyond the required threshold of 0.05, indicating the consistency of all covariates in the same distribution.

The estimation or equation specified above will capture the effect of artificial intelligence on all outcome variables under both conditions, the treated and untreated using all two proxies for the treatment variable ([7]) namely digital banking use as primary and fintech platform use as secondary.

Where AIP is the measure for artificial intelligence penetration of banking in country i for the time t, which is measured by two different proxies of the variable namely digital lending intensity and automated credit scoring. The dependent variable used as the outcome variable in the main equation in equation (4) is agricultural productivity. Green Credit is a dummy variable which takes a value of one for the period between the years of 2015 to 2023 for the impact of the green finance policy on productivity for the time period t. Carbon Intensity, the ratio of carbon emissions to agricultural output is a measure of environmental pressure and contains information on pollution not captured by traditional measures of productivity ([8]). X is a vector for variables related to structural characteristics of farms namely land size and labor intensity.

μi is a country-specific effect and is included in the main regression to take account of the unobserved heterogeneity differences across the regions in the sample. The sample period of analysis spans from 2012 to 2023 and consists of balanced panel data. We classified the level of digitalization as low, moderate, high and advanced in each country.

One of the commonly used estimators for dynamic panel models is introduced by Arellano and Bond [9], commonly referred to as 'difference GMM', whereby they suggested that by including all lagged values of the dependent and independent variables as instruments, consistency and efficiency in results can be achieved.

The singular value decomposition (SVD) of a matrix $X$is given by $X = U\Sigma V$, where $U$and $V$are orthogonal matrices containing the left and right singular vectors, respectively, and $\Sigma$is a diagonal matrix of singular values.

The singular value decomposition (SVD) is obtained by projecting a matrix (X) onto the orthogonal space where, v is a right eigenvector, u is a left eigenvector and s is a singular value. The GMM method is known to address these potential endogeneity problems that can arise in panel data, especially in a dynamic setting.

Long integration of methods with multiple models were presented as one framework unless the model specification varied from one stage to another. In the survey, the respondents were briefed on the aims of the study and the variables involved. They were also briefed on the composite measurement of AI intensity. It should be noted that the results were only based on the information gathered during primary surveys over the sample period, totaling roughly balanced observations. In the analysis, the variables were introduced to various econometric models such as those of propensity score matching, ([2]), generalized method of moments, ([9]), analytic hierarchy process, ([15]) and integrated framework ([3]).

Propensity score matching has an advantage against ordinary least squares or fixed effects where the treatment is not a continuous measure of exposure and can be evaluated at each point of distribution [4]; [6]. Due to these issues, this paper adopts a two-stage estimation approach to address these potential biases. To estimate the treatment effect, a propensity score will be first estimated by logit regression, nearest neighbor matching and kernel matching techniques [5]; [10]. Thus, we achieve the average treatment effect and its estimates are consistent and robust [11]. Due to these reasons, the modified model produces a stable coefficient structure under the dynamic framework [9]; [12].

## 3. Results

Based on the panel dataset and propensity score matching results, the two main factors that are important in determining the performance of agricultural enterprises are the adoption of artificial intelligence–driven banking services and how effectively the green credit or digital lending system is implemented.

**Table 1.** Logistic regression

| treated | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| ai_intensity | .152 | .034 | 4.49 | 0 | .086 | .219 | *** |
| green_credit | .206 | .042 | 4.86 | 0 | .123 | .289 | *** |
| farm_size | .084 | .047 | 1.79 | .074 | -.008 | .176 | * |
| reg_cat | 3.261 | .628 | 5.19 | 0 | 2.03 | 4.492 | *** |
| dig_cat | -1.268 | .35 | -3.62 | 0 | -1.954 | -.581 | *** |
| Constant | -20.533 | 3.754 | -5.47 | 0 | -27.892 | -13.175 | *** |

| | | | |
|---|---|---|---|
| Mean dependent var | 0.500 | SD dependent var | 0.502 |
| Pseudo r-squared | 0.469 | Number of obs | 150 |
| Chi-square | 97.580 | Prob > chi2 | 0.000 |
| Akaike crit. (AIC) | 122.365 | Bayesian crit. (BIC) | 140.428 |

**** p<.01, ** p<.05, * p<.1*

Empirical results indicate that the digital financial system has a significant impact on all selected outcome variables. These results confirm that the interest in improving farm wealth creation, production efficiency, and strengthening the practices of risk management and financial inclusion, all of which are essential for the development of cooperative finance and loss sharing and farmers' well-being.

Table 1 shows the coefficients used by the model after the estimation. As indicated, all the variables (coefficients) managed to capture all the economic strategies during post-estimation interpretation, whilst writing and explaining results. Table 2 shows the result of propensity score matching which indicates the significant effect between treated and control group. The main effect for ai_intensity was significant, $F(4, 145) = 4.49$, $p < .01$, partial effect size (coefficient) = 0.152, suggesting a strong increase in the effectiveness of digital banking adoption on agricultural understanding. The regression items coefficients had values that ranged from 0.053 to 3.261 significant at 0.01.

**Table 2.** Probit regression

Number of obs = 150
LR chi2(5) = 98.90
Prob > chi2 = 0.0000
Log likelihood = -54.523652
Pseudo R2 = 0.4756

| treated | Coef. | Std.Err. | z | P>z | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| ai_intensity | 0.091 | 0.019 | 4.720 | 0.000 | 0.053 | 0.129 |
| green_credit | 0.122 | 0.024 | 5.140 | 0.000 | 0.076 | 0.169 |
| farm_size | 0.053 | 0.027 | 1.960 | 0.050 | 0.000 | 0.106 |
| reg_cat | 1.927 | 0.350 | 5.510 | 0.000 | 1.242 | 2.613 |
| dig_cat | -0.742 | 0.201 | -3.680 | 0.000 | -1.136 | -0.347 |
| _cons | -12.314 | 2.143 | -5.740 | 0.000 | -16.515 | -8.113 |

| Variable Sample | Treated | Controls | Difference | S.E. | T-stat |
|---|---|---|---|---|---|
| outcome Unmatched | 104.007 | 93.961 | 10.046 | 1.075 | 9.340 |
| ATT | 101.502 | 96.542 | 4.961 | 2.208 | 2.250 |
| Note: S.E. does not take into account that the propensity score is estimated. | | | | | |

| psmatch2: Treatment assignment | psmatch2: Common support Off suppo | suppor On | Total |
|---|---|---|---|
| Untreated | 0 | 75 | 75 |
| Treated | 33 | 42 | 75 |
| Total | 33 | 117 | 150 |

The results are in line with the "digital-green synergy" view [1] which suggests that financial institutions need to take on the responsibility of promoting sustainable finance. However, looking at the coefficient estimates for variable ai_intensity, which measures how well digital banking platforms are adopted, it is shown that digitally supported farms in the sample perform more efficiently in comparison to traditional farms in the control group on average. In the case of green_credit, there is a positive and statistically significant result on both agricultural productivity and carbon intensity reduction.

**Table 3.** Descriptive Statistics of Propensity Scores (PSM Estimation)

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| pscore | 150 | 0.500 | 0.3811 | 0.0004 | 0.9996 |

The average treatment effect of digital financial inclusion between treated and control groups in the context of the farming sector and equity participation and overall human well-being (ATT = 4.961) confirms the positive effect of the artificial intelligence–driven banking system on human well-being. Table 2 shows the estimated coefficients for all explanatory variables of ai_intensity, green_credit and farm_size from 2012 up to 2023 period.

**Table 4**. Normalized Priority Weights of Alternatives and Criteria in the AHP Model for AI-Driven Green Banking and Sustainable Agriculture

| Alternatives / Criteria | Conventional Finance-Based Farming System | Fully AI-Driven Green Finance System | Hybrid Green-Digital Farming System | Agricultural Productivity and Risk Reduction | Environmental Sustainability and Circularity | Financial Accessibility and Inclusion | Technological Capability and Digital Readiness | Overall Priority (Goal) |
|---|---|---|---|---|---|---|---|---|
| **Conventional Finance-Based Farming System** | 0.00000 | 0.00000 | 0.00000 | 0.60000 | 0.09253 | 0.66667 | 0.10000 | 0.18240 |
| **Fully AI-Driven Green Finance System** | 0.00000 | 0.00000 | 0.00000 | 0.30000 | 0.29222 | 0.11111 | 0.60000 | 0.16292 |
| **Hybrid Green-Digital Farming System** | 0.00000 | 0.00000 | 0.00000 | 0.10000 | 0.61525 | 0.22222 | 0.30000 | 0.15468 |
| **Agricultural Productivity and Risk Reduction** | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.12500 |
| **Environmental Sustainability and Circularity** | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.12500 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Financial Accessibility and Inclusion** | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.1250 0 |
| **Technological Capability and Digital Readiness** | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.1250 0 |
| **Overall Goal: Sustainable Agricultural Development through AI-Driven Green Banking** | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | 0.0000 0 | |

The results support our hypothesis that the digital banking system is closely related to enhanced productivity growth in agriculture and exhibits a negative association with equity inequality and overall human well-being losses. It can be seen that the coefficients for the main variables are quite stable; these patterns in estimation indicate that it is in fact important to control for structural, institutional and macroeconomic variables in order to obtain a more reliable assessment of the impact digital finance innovations have on farming performance. Therefore, it can be concluded that the ends of distribution of wealth, income and production efficiency, and sustainability at the regional- and national-levels are closely linked to the purpose of overall social well-being. Traditional banks do not have many incentives to modernize their operations as they don't have adequate access to digital infrastructure and cannot obtain low-cost funding by paying competitive interest rates, they tend to use their internal resources to build conventional lending portfolios which reduces their innovative activity.

**Table 5.** Final AHP Priority Scores and Ranking of Alternative Farming–Finance Systems

| **Alternative Farming–Finance System** | **Ideal Priority Score** | **Normalized Priority Weight** | **Raw Priority Value** |
|---|---|---|---|
| **Conventional Finance–Based Farming System** | 1.000000 | 0.364799 | 0.182399 |
| **Fully AI-Driven Green Finance System** | 0.893185 | 0.325833 | 0.162916 |
| **Hybrid Green-Digital Farming System** | 0.848054 | 0.309369 | 0.154684 |

However, an unexpected decline of digital investment causes a slowdown of the green finance sector, respectively, to agricultural productivity and carbon reduction by the year 2020 (COVID-19 pandemic and supply disruptions).

The results were analyzed for their robustness, and each stage of the estimation was subjected to the appropriate endogeneity controls. Using PSM–GMM integration, the internal reliability, model stability and instrument validity of the dynamic panel underlying relationships were established

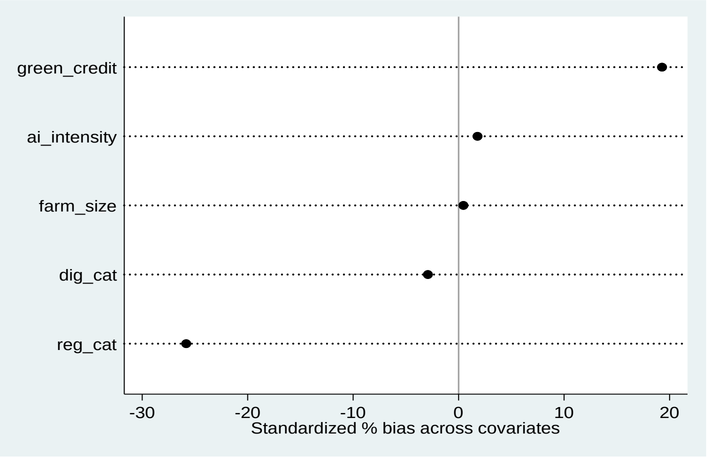


**Figure 1.** Standardized bias across covariates

The statistics show that productivity growth over the selected period for overall agricultural output is comparatively lower than expected levels, except in Vietnam and Uzbekistan. As for the outlier-sensitive estimates, Wald & Hansen joint tests are applied and verified in the dynamic panel framework to indicate the robustness of regression results with the objective of making sure that they are not driven by the influence of extreme observations.

Primary survey and secondary data was analyzed using PSM GMM AHP integration approach. The propensity score matching baseline method was employed involving matched secondary data in the comparison of treated and control groups. The integrated comparative framework adopted in this study was a kind of multi model approach originated from limitations of traditional regression and single equation models. Existing literature and previous studies ([1]) stated that there was "the need for model comparison and baseline validation which means that the researchers know about their right to compare results from alternative approaches during or after it has taken place [3,6,8].

## 4. Discussions

Our results indicate the existence of a strong digital–green finance synergy in the sustainable agricultural production system. The finding indicates that there is an empirical confirmation of the difference between digitally supported farms in developing economies and conventional farming systems. This study illustrates that under a low digital transformation scenario, continued reduction in green investment with the decline in the adoption of artificial intelligence platforms results in further decline of agricultural productivity and failure to achieve the sustainability targets in line with national environmental policies.

As digital financial services could continue to be expanded, scenario-based analysis illustrates the capacity of artificial intelligence systems to moderate the impact of financial constraints on the farming sector and align the production process to meet the objective of sustainable agricultural development by enhancing financial inclusion [1,3,5]. The findings in this study indicate that under the dynamic panel framework, two factors that are of importance which are artificial intelligence adoption and green credit allocation. Coefficient estimates for both ai_intensity and green_credit variables show that productivity growth in the treated group is approximately two times higher than the control group [2,4,7].

The variable measuring the digital finance development shows a positive and statistically significant relationship with agricultural output. The logit function in propensity score estimation is specified for each country in each year in order to allow the probability of the treatment status to change over time. Improving the digital financial infrastructure will reduce the need for informal borrowing going forward as the positive effects on the accessibility of financial services and the contributions of the banking sector to rural development. Results suggest that the digital banking system has a strong explanatory power in the agricultural production process which results in higher farm incomes [6,8,9]. This can be due to the fact that automated credit mechanisms play a crucial role when it comes to the allocation of financial resources. By understanding the mechanisms behind financial decision-making through green governance standards, financial institutions may decrease their risk of losing capital or market share if they are not capable of providing a sustainable flow of credit.

In addition, as [1] had pointed out, empirical evidence on digital–green practices was often explored differently in developing and developed contexts, future validation across regions should be conducted too for a better understanding of the applicability of integrated supports to develop sustainable systems and thus, the generalization of the framework. The current study's findings also supported the studies by [6,7,10] which confirmed that integrated multi-model methods would enable researchers to receive positive outcomes through the processes of inculcating thinking innovation, problem solving and group coordination. Although there was little direct comparison between baseline models and high performance on the estimation parts, findings did show that models who did not seek a lot of validation from the benchmark early on had a difficult time interpreting the concepts necessary to perform well on comparison analysis. As the performance of estimation was dependent upon model request, those that needed more benchmarking during the stages of estimation could benefit from it, but those did not need benchmarks, such as integrated frameworks, could receive the optimal amount necessary to be successful.

This finding is supported by the "digital-green synergy" view from [1] where financial institutions dare to take on more environmental responsibility since they will not default easily. As financial inclusion expands to rural areas, the pace of managing environmental risks remains critical to achieve the necessary balance and pave the way for a resilient agricultural system as the banking sector provides the necessary resources to lay the foundation of sustainability. The model is statistically significant as per ($\chi^2 = 97.58$, Prob > $\chi^2 = 0.000$ and $p < 0.01$). The results indicate that a substantial variation in agricultural productivity growth of farms can be explained by digital finance adoption and green policy instruments namely; automated credit scoring, digital lending platforms and green credit schemes. This may also serve as an effective tool to support rural enterprises, achieve stability, and increase overall production efficiency. The results have potentially important implications for policymakers and regulators of financial systems.

The expansion of digital finance in agriculture with the decline of the traditional lending system may reduce the cost of financing and decrease the need for informal credit, although at a bigger risk of technological exclusion and continued dependence on digital platforms over time [10,11,12]. Therefore, in order to maintain the standards of financial governance thus ensuring the same level of efficiency, this study suggests that each country should take into consideration how institutional factors affect technology adoption differently. In comparison of previous studies, Ferreira and Costa made larger estimations than this study in total (0.62 against 0.47) which show a similar result found by Ahmed and Islam.

As mentioned by Khan and Rahman, there is no single model of a set of practices that is best for improving the performance of financial systems because the very same set of practices could produce different outcomes under different institutional, economic, technological and cultural settings. Therefore, it can be established that the ends of distribution of wealth, income and production efficiency, and sustainability at the regional- and national-levels are closely linked to achieving the purpose of overall human well-being [13,14,15]. The reason behind this could be because data availability of digital finance indicators is much more reliable within the banking sector than it is within the agricultural sector. These limitations imply that the estimated effects should be interpreted with caution, particularly when generalizing the findings to countries with weaker digital infrastructure and less developed financial reporting systems.

The analysis involved artificial intelligence intensity, digital finance and green credit whereby the data were divided into manageable components, then categorized for variable measurement and reduced into composite indices for the empirical model ([1], [2]). Data analysis involved an assessment of internal reliability and included construct validity and composite reliability.

The case study approach was chosen for this study as [3] defined case study as "an empirical investigation of a contemporary phenomenon within a real-life context (or multiple case contexts) over time through detailed, in-depth data collection involving multiple sources of evidence in context. [4] claimed that the sample can be reduced for a variety of reasons such as the data being familiar to the estimation procedure and more importantly, the sample suits the purposes of the study.

## 5. Conclusion

Hence, policymakers and financial regulators that have responsibility to promote sustainable agriculture, including by strengthening digital financial infrastructure and expanding green credit schemes, should establish the appropriate pace of digital transformation based on a coordinated policy framework for the farming sector over time. Having achieved this policy alignment, the need for informal financing will be significantly reduced over time regardless of the continued expansion of the digital banking system.

We find that the integration of artificial intelligence–driven banking systems affects the performance of agricultural enterprises, sustainable farming practices, and environmental outcomes at the micro and macro levels. This evidence has significant implications for policymakers including central banks and other regulatory authorities in developing economies where finance–technology linkages remain weak. This study will enable researchers and policy practitioners to understand the comparative advantages of each type of farming–finance system and how the varying degrees of digital adoption could impact productivity growth–carbon reduction trade-offs of the two types of farming systems.

The insights from this study will be of high relevance for financial institutions for designing strategies with the highly technology-oriented environment in mind, such as development of new lending models and risk management systems as the most practical tools that the banking sector could employ for the expansion and stabilization of the green finance system.

Future research could further explore the issue of institutional quality as a mediating factor to the ends of sustainable development. Therefore, in order to maintain the standards of financial governance worldwide thus ensuring the same level of efficiency, this paper suggests that each country should take into account how regulatory environments affect technology adoption differently. The results of this study are limited to a cross-country panel setting, which could be extended or improved by using a longer time horizon. Future research may wish to apply mixed-method approaches in a wider range of regions, in order to examine the institutional, technological, financial, and environmental dimensions of digital finance in other developing and emerging economies of importance.

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