



DIGITAL CREDIT ALGORITHMS AND AGRIPRENEURS' ACCESS TO FINANCE IN SUB-SAHARAN AFRICA: EVALUATING MOBILE MONEY TRANSACTION HISTORIES AS COLLATERAL SUBSTITUTES

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ABSTRACT

In Sub-Saharan Africa, many smallholder farmers struggle to obtain loans because traditional lenders require collateral, which these farmers often lack. However, with the rise of mobile money, there is a new opportunity to assess creditworthiness. This study explores whether mobile money transaction histories can substitute traditional collateral in digital credit algorithms, potentially helping agripreneurs access finance. The research examines data from four countries: Kenya, Ghana, Nigeria, and Cameroon, involving 2,400 agripreneurs and over 847,000 mobile money transactions. Interviews with 60 agripreneurs, 24 lenders, and 16 regulators were conducted for deeper insights. The quantitative data were analyzed using random forest machine learning models, logistic regression, and propensity score matching, while qualitative data were analyzed using thematic analysis. The results showed that mobile money transaction history-based credit scores predicted loan repayment with 78.3% accuracy, comparable to traditional collateral-based assessments but with higher inclusion rates. Borrowers approved through the algorithm had similar default rates to those approved through traditional assessments. Despite positive findings, challenges such as algorithm distrust and regulatory gaps remain. Recommendations include establishing regulatory sandboxes, mandating transparency disclosures, developing value chain-specific scoring models, implementing consumer education programs, and creating portable credit reputation systems across FinTech providers. Overall, mobile money transaction histories could significantly benefit agripreneurs in Sub-Saharan Africa by improving access to finance, provided appropriate regulations and safeguards are implemented.

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1.0 Introduction

Access to formal credit remains a persistent constraint for agripreneurs in Sub-Saharan Africa. Smallholder farmers and agricultural entrepreneurs, who constitute approximately 60% of the region's workforce, are systematically excluded from traditional banking systems due to their inability to provide physical collateral such as land titles, vehicles, or buildings (Demirgüç-Kunt et al., 2022). This collateral requirement creates a paradox: the farmers who most need credit to invest in productivity-enhancing inputs are those least able to access it, perpetuating cycles of subsistence agriculture and poverty (Ky, 2025).

The issue is significant. In Sub-Saharan Africa, approximately 44% of adults lack bank accounts, most of whom are rural farmers (Demirgüç-Kunt et al., 2022). The financial gap for small farmers exceeds \$65 billion annually (World Bank, 2026a). Consequently, farmers unable to access credit underutilize fertilizers and better seeds, resulting in crops that are 30-50% less productive than their potential (World Bank, 2026a). Digital credit offers a new avenue for obtaining loans via mobile phones, utilizing algorithms to assess creditworthiness rather than requiring traditional collateral. This shift is significant for many, especially African farmers, who lack the assets that conventional lenders demand. By leveraging mobile phone payment history, digital credit can potentially reach the 57% of African farmers already using mobile money (GSMA, 2024), enabling them to access the necessary credit to grow their businesses without traditional collateral. This development could significantly benefit those excluded from traditional banking. Digital credit providers can extend loans to previously underserved individuals, potentially transforming their lives.

However, the situation is complex. Despite rapid growth in digital credit, with companies like M-Shwari in Kenya, Carbon in Nigeria, and Branch across Africa issuing millions of loans, farmers remain underserved (Björkegård, 2025). The algorithms designed for salaried, urban individuals do not align with the income patterns

of farmers, who earn seasonally with crop harvests (Ky, 2025). Consequently, farmers face lower approval rates, smaller loan amounts, and higher interest rates than their urban counterparts (Klapper & Tellez-Merchan, 2026). This study addresses whether mobile money transaction histories can serve as valid collateral substitutes in digital credit algorithms for agripreneurs. For data to function as a collateral substitute, it must meet three criteria: (a) predict repayment behavior with acceptable accuracy, (b) avoid systematic discrimination against disadvantaged groups, and (c) earn agripreneurs' trust and understanding of the algorithmic scoring process (Chopra et al., 2024).

While mobile money and creditworthiness are connected, the relationship is not fully understood. Some studies in Kenya have suggested that mobile money usage frequency, savings levels, and airtime purchase regularity can indicate credit management (Jack & Suri, 2011; Suri & Jack, 2016). However, these studies focused on the general population, not specifically on farmers or agricultural businesses. Lending to farmers is challenging due to income variability from factors like seasonality and weather, complicating loan repayment predictions (Wahbi & Musshoff, 2024). Concerns also exist that credit algorithms might be biased against women and rural individuals, potentially excluding them from loans and worsening their financial situation (Chopra et al., 2024). Further research is needed to understand how mobile money transaction patterns can determine creditworthiness, particularly for farmers and agricultural businesses, while addressing fairness and transparency issues in digital credit algorithms.

Sub-Saharan Africa offers a unique context for studying digital credit algorithms and collateral substitutes. The region has leapfrogged traditional banking, leading the world in mobile money with over 621 million active accounts (GSMA, 2024). As a result, extensive mobile money transaction data is readily available. Simultaneously, accessing loans from traditional banks remains challenging for farmers most banks allocate less than 5% of their funds to agriculture (World Bank, 2026a). This makes

Sub-Saharan Africa an intriguing place to explore how digital credit can bridge the gap.

This research examines four Sub-Saharan African countries at different stages of digital credit development: Kenya, Nigeria, Ghana, and Cameroon. Kenya is the most advanced, with popular services like M-PESA and M-Shwari. Nigeria, with the largest market, is experiencing rapid FinTech growth. Ghana's digital credit market is emerging, with a strong digital presence in its cocoa industry. Cameroon leads in mobile money in Central Africa. By studying these countries, we can compare how different regulations, mobile money platforms, and industries like agriculture utilize digital credit. Therefore, this study aims to fill the existing research gap by examining whether mobile money transaction histories can serve as valid collateral substitutes in digital credit algorithms to enhance Agripreneur access to finance in Sub-Saharan Africa. Specifically, the study aims to:

- i. Assess the predictive accuracy of mobile money transaction history-based algorithmic credit scores for agripreneur loan repayment across Sub-Saharan Africa.
- ii. Analyze how specific patterns in mobile money transactions, including transaction frequency, savings consistency, airtime purchase behavior, and transaction reversals, affect agripreneurs' likelihood of loan repayment.
- iii. Compare loan approval rates, loan sizes, interest rates, and default rates between algorithm-based and collateral-based lending for agripreneurs.
- iv. Identify the barriers of Agripreneur acceptance of algorithm-driven digital credit, including trust, transparency, and understanding.
- v. Evaluate the regulatory frameworks governing digital credit algorithms for agricultural lending across selected Sub-Saharan African countries.

2.0 Literature Review

2.1 Conceptual Review

Digital Credit

Digital credit refers to loans that are approved, disbursed, and repaid entirely through digital channels, primarily mobile phones, without the involvement of loan officers, physical paperwork, or traditional collateral requirements (Björkegård, 2025). This represents a fundamental departure from conventional lending models, as the entire credit process from application to disbursement to repayment occurs digitally, often within minutes.

Björkegård (2025) conceptualizes digital credit as operating through three interconnected stages. The first stage involves **data collection**, where lenders gather information from mobile network operators, FinTech platforms, and other digital sources to build a comprehensive profile of the potential borrower. The second stage involves **algorithmic scoring**, where machine learning models trained on historical repayment data generate credit scores that predict the likelihood of loan repayment. The third stage involves **automated loan origination and servicing**, where approved loans are disbursed instantly and repayments are collected automatically through digital channels.

The defining characteristic of digital credit is its **automation**. Unlike traditional lending, where loan officers exercise discretion in evaluating applications, digital credit relies entirely on data-driven algorithms to make lending decisions. This automation removes human bias from the lending process but also introduces new concerns about algorithmic fairness and transparency (Chopra et al., 2024). Digital credit has expanded rapidly across Sub-Saharan Africa, with over 150 million loans originated by 2024 (Björkegård, 2025). The growth has been particularly pronounced in countries like Kenya, where M-Shwari and Fuliza have become household names, and Nigeria, where platforms like Carbon and FairMoney have gained substantial market penetration. However, the agricultural sector remains underserved despite this rapid expansion, as digital credit products were predominantly

designed for salaried, urban consumers with regular income patterns (Ky, 2025).

In my understanding, digital credit represents a fundamental shift from relationship-based lending to data-driven lending, where the quality and comprehensiveness of digital footprints determine credit access. This shift has profound implications for financial inclusion, as it potentially democratizes access to credit by removing traditional barriers such as physical collateral, formal employment documentation, and banking history. However, this democratization is conditional: individuals must have sufficient digital footprints to be scored, which may exclude the most marginalized populations who are not active digital users. The challenge for agricultural lending is particularly acute, as the seasonal, irregular income patterns characteristic of farming are poorly captured by algorithms trained on urban, salaried populations.

2.1.2 Algorithmic Lending

Algorithmic lending refers specifically to the use of automated computational systems to assess creditworthiness and make lending decisions, typically as a component of the broader digital credit ecosystem (Ambler et al., 2025). While digital credit encompasses the entire lending process application, disbursement, servicing, and repayment algorithmic lending focuses specifically on the decision-making mechanism that determines who receives credit and on what terms.

The **algorithm** in algorithmic lending is a set of computational rules, typically based on machine learning models, that analyzes multiple data points to generate a credit score or risk assessment (Björkegård, 2025). These algorithms are trained on historical data past loan performance, repayment patterns, and default histories to identify statistical relationships between borrower characteristics and repayment outcomes. Once trained, the algorithm applies these learned patterns to new applicants to predict their likelihood of repayment.

Algorithmic lending operates through several key mechanisms. First, it utilizes **alternative data sources** beyond traditional credit bureau information. These data sources include mobile money transaction histories, airtime purchases, social media activity, phone usage patterns, and even device metadata such as phone model and charging habits (Ambler et al., 2025). Second, it employs **machine learning techniques** such as random forests, gradient boosting, and neural networks to identify complex, non-linear relationships in the data that traditional credit scoring models might miss. Third, it enables **real-time decision-making**, as algorithms can process applications and generate credit decisions within seconds or minutes.

The theoretical foundation of algorithmic lending lies in addressing **information asymmetry** the situation where borrowers know more about their own creditworthiness than lenders do (Stiglitz & Weiss, 1981). In traditional lending, physical collateral mitigates this asymmetry by providing lenders with a form of security. In algorithmic lending, digital footprints serve as information signals that reduce the information gap between borrowers and lenders (Björkegård, 2025). The adoption of algorithmic lending has been driven by its potential to **expand credit access**. By using alternative data sources, algorithms can assess the creditworthiness of individuals who lack formal credit histories, thereby extending credit to previously underserved populations (Klapper & Tellez-Merchan, 2026). This is particularly significant in Sub-Saharan Africa, where the majority of adults lack formal bank accounts or credit bureau records (Demirgüç-Kunt et al., 2022).

However, algorithmic lending also introduces significant challenges. First, there are **concerns about algorithmic bias** the possibility that algorithms may systematically disadvantage certain groups, such as women or rural populations, if the training data reflects existing inequalities (Chopra et al., 2024). Second, there are **transparency concerns**, as borrowers often do not understand how their credit scores are calculated or why they were approved or rejected (Bongomin et al., 2025, 2026). Third, there are **regulatory gaps**, as many countries lack specific

regulations governing algorithmic lending, particularly regarding data protection, algorithm transparency, and consumer recourse (Björkegård, 2025).

In my assessment, algorithmic lending represents a double-edged sword for financial inclusion. On one hand, it has the potential to dramatically expand credit access by replacing rigid, collateral-based lending criteria with flexible, data-driven assessments. On the other hand, it risks creating new forms of exclusion for individuals whose digital footprints are limited or whose transaction patterns differ from those of the urban populations on which algorithms were trained. The challenge for agricultural lending is particularly acute, as farmers' seasonal, irregular transaction patterns may be misclassified as risk indicators by algorithms that expect stable, regular income flows. This highlights the need for agriculture-specific algorithms that account for seasonality, income volatility, and value chain differences a finding supported by Waldron et al. (2026), who demonstrated that different transaction patterns predict creditworthiness for different agricultural populations.

The relationship between digital credit and algorithmic lending is interdependent: digital credit relies on algorithmic lending as its decision-making engine, while algorithmic lending finds its primary application within the digital credit ecosystem. In the context of this study, algorithmic lending is the mechanism through which mobile money transaction histories are evaluated as potential collateral substitutes. Therefore, understanding the capabilities and limitations of algorithmic lending is essential for assessing whether digital credit can serve as a viable alternative to traditional collateral-based lending for agripreneurs.

Mobile Money Transaction Histories as Alternative Data

Mobile money transaction history records all financial activities on the platform, including deposits, withdrawals, transfers, airtime purchases, and bill payments. Lenders value this

history as it reflects financial management. Key aspects include income and expenditure frequency, savings behavior, and debt repayment reliability. This information helps lenders decide on future lending. Klapper and Tellez-Merchan (2026) proposed viewing mobile money transaction histories as "digital collateral substitutes." These records provide financial management evidence, unlike tangible collateral, which can be seized if a loan defaults. Digital footprints, while not seizable, indicate financial responsibility. If borrowers are responsible in the past, they are likely to be responsible in the future. This approach assists lenders in assessing loan candidates. My assessment is that the concept of digital collateral substitutes challenges the traditional banking paradigm, shifting focus from what borrowers *own* to what they *do*. This behavioral approach to credit assessment has the potential to unlock credit for millions of unbanked individuals.

Collateral Substitutes in Agricultural Finance

Traditional lending theory holds that collateral addresses adverse selection and moral hazard problems (Stiglitz & Weiss, 1981). Borrowers with collateral have "skin in the game," reducing their incentive to default. For agripreneurs lacking physical collateral, various substitutes have been proposed, including group lending, social capital, and interlinked transactions (Wahbi & Musshoff, 2024). Researchers like Waldron et al. (2026) found digital credit algorithms can help lenders make decisions without physical collateral. This is especially beneficial for agricultural entrepreneurs, as past transactions reflect financial management. By analyzing these transactions, algorithms reduce lender uncertainty, aiding informed lending decisions without physical collateral. This data-driven approach addresses borrower information gaps. I contend that mobile money transaction histories are uniquely suited as collateral substitutes for agripreneurs because they capture the irregular, seasonal income patterns characteristic of agricultural livelihoods, potentially enabling more accurate risk assessment than traditional approaches.

2.2 Theoretical Review

2.2.1 Financial Inclusion Theory

Financial inclusion theory posits that access to appropriate financial services enables poor households to manage risk, smooth consumption, and invest in productive activities (Jack & Suri, 2011; Suri & Jack, 2016). Ndip and Kemeni Kambiet (2026) extend this theory to digital credit, arguing that algorithmic lending can dramatically expand financial inclusion by removing collateral barriers. This extension operates through two main methods. Firstly, a special scoring system enhances lender understanding, enabling them to assist previously ineligible individuals by addressing information gaps. Secondly, it creates a digital transaction record, facilitating future credit access. This creates a cycle where obtaining credit eases future credit access. For example, Ky's (2025) analysis of farming found limited mobile money usage impeding digital credit access. This theory is directly relevant to this study because it provides the overarching framework for understanding *why* expanding credit access matters: it enables investment, risk management, and poverty reduction among agripreneurs.

2.2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), explains technology adoption through perceived usefulness and perceived ease of use. Bongomin et al. (2025, 2026) applied TAM to mobile banking adoption among agri-entrepreneurs, identifying awareness as the strongest predictor. Chopra et al. (2024) identified distrust in computer-generated decisions, even if superior to human ones. They updated an existing theory to explain this. Now, acceptance of computer-made decisions requires trust, understanding, and perceived fairness. This is crucial for digital credit, where computers determine loan eligibility. If decision-makers distrust or misunderstand the computers, they may avoid using them, despite their efficacy. This theory is relevant because it provides a framework for understanding agripreneurs' acceptance of algorithmic credit decisions,

particularly the psychological barriers (algorithm aversion) that may limit adoption.

2.2.3 Transaction Cost Economics

Transaction cost economics, developed by Coase (1937) and Williamson (1975, 1985), explains economic organization as a response to transaction costs. Ambler et al. (2025) apply this framework to digital credit, arguing that algorithms reduce the transaction costs of credit assessment. In traditional lending, transaction costs include search costs (finding creditworthy borrowers), information costs (verifying income and assets), and enforcement costs (collecting on defaults). Digital credit algorithms reduce these costs by automating information collection and analysis. However, Wahbi and Musshoff (2024) note that new transaction costs emerge, including the cost of understanding algorithm decisions and the risk of algorithmic error. This theory connects to this study by explaining the efficiency rationale for digital credit adoption, while also highlighting potential new frictions.

2.2.4 Signaling Theory and Digital Footprints

Signaling theory, developed by Spence (1973), explains how individuals convey unobservable characteristics through observable signals. In credit markets, borrowers signal their creditworthiness through behaviors that are costly to fake (Stiglitz & Weiss, 1981). Björkegård (2025) applies signaling theory to digital credit, arguing that mobile money transaction histories serve as costly signals of creditworthiness. Consistent savings behavior signals financial discipline. Regular airtime purchases signal stable income. The absence of reversed transactions signals reliability. These signals are credible because they are costly to produce and difficult to manipulate. This theory is relevant because it provides the micro-foundations for understanding why mobile money transaction patterns can predict creditworthiness: they are observable, costly-to-fake signals of underlying creditworthiness.

The Underpinning Theory for the Study

This study is underpinned by **Signaling Theory** as developed by Spence (1973) and extended to credit markets by Stiglitz and Weiss (1981). I justify this choice for several reasons. First, signaling theory provides the most direct explanation for *how* mobile money transaction histories can function as collateral substitutes: they are observable signals that convey unobservable characteristics of creditworthiness. Second, unlike TAM, which focuses on adoption, or transaction cost economics, which focuses on efficiency, signaling theory explains the fundamental information problem that digital credit algorithms address. Third, the theory generates testable predictions about which transaction patterns should be most predictive of creditworthiness (those that are most costly to fake and most difficult to manipulate). This theoretical lens is particularly apt for understanding whether and how mobile money data can substitute for traditional collateral, as it identifies the conditions under which signals are credible. The AIDA model, while useful for marketing contexts, does not address the information asymmetry problems central to credit markets. Similarly, while financial inclusion theory provides the motivation for expanding credit access, signaling theory provides the mechanism by which digital credit achieves this expansion.

2.3 Empirical Review

Chopra et al. (2024) found that distrust in algorithmic loan decisions was prevalent—62% of respondents expressed discomfort with computers determining loan access. Concerns included lack of understanding, fear of errors, and absence of human interaction for problem resolution. However, explaining algorithmic decisions and providing score feedback increased trust. This is highly relevant as it demonstrates that algorithm aversion is not unique to Africa and that transparency interventions can help.

Ambler et al. (2025) found that maintaining good relationships with financial agents was crucial. In Nigeria, trust in mobile money agents increased

acceptance of algorithmic credit offers. Agents who explained algorithmic decisions reduced fear, indicating that trusted intermediaries can facilitate technology adoption. In my view, this highlights the importance of the human element even in digital processes, suggesting that successful digital credit deployment requires a hybrid approach.

Björkegård (2025) conducted a regulatory review across 12 Sub-Saharan African countries, finding substantial variation in digital credit governance. Kenya has the most developed framework, with the Central Bank requiring algorithm transparency, interest rate caps, and consumer complaint mechanisms. Nigeria has emerging regulations focusing on data protection. Ghana and Cameroon have limited specific regulations, with digital credit governed by general consumer protection laws. This study provides a benchmark for assessing regulatory development across the four countries. The study identified four regulatory gaps: (a) no requirements for algorithm transparency or explainability, (b) no standards for alternative data quality, (c) limited consumer recourse mechanisms, and (d) no agriculture-specific provisions for seasonality or weather shocks. These gaps are directly relevant to this study's objective of evaluating regulatory frameworks.

In contrast, Ky (2025) found that while mobile money data predicts repayment for urban borrowers, accuracy declines for rural agricultural borrowers due to income seasonality. Farmers with highly variable transaction patterns were misclassified as high-risk despite being reliable borrowers during harvest seasons. The study recommended developing agriculture-specific algorithms that account for seasonality. This finding is particularly relevant to this study, as it highlights the need to specifically examine agripreneurs rather than general populations. Connecting these studies, I observe that the literature presents a nuanced picture: mobile money data is generally predictive, but its predictive power varies by borrower type and context. This suggests that a study specifically focused on agripreneurs, using country-comparative data, can make a valuable contribution.

Waldron et al. (2026), studying cocoa farmers in Ghana, found that different transaction patterns predict creditworthiness in agricultural versus non-agricultural populations. For cocoa farmers, the timing of savings accumulation (building reserves before harvest) was more predictive than absolute savings levels. Airtime purchase regularity predicted repayment better for maize farmers than for cocoa farmers. This finding is crucial because it suggests that one-size-fits-all algorithms may underperform in agricultural contexts. In my assessment, the literature on transaction patterns is converging on the importance of consistency and regularity as signals of creditworthiness, but the specific metrics that matter may vary by agricultural context. This study aims to extend this by comparing across multiple value chains and countries.

Klapper and Tellez-Merchan (2026) analyzed Global Findex 2025 data, finding that algorithmic digital credit increased loan access, especially for the unbanked. In countries with prevalent digital credit, mobile money users had a 45-60% loan approval rate, compared to 15-25% through traditional banks. However, algorithm-based loans were smaller (\$50 vs. \$500) and had higher interest rates (15-30% vs. 5-15%). This shows digital credit boosts loan access but with significant differences in loan size and cost. This study's findings on loan size and interest rate differentials can be compared to these benchmarks.

Ndip and Kemeni Kambiet (2026) analyzed digital credit borrowing in Cameroon, finding similar default rates (12-15%) for both digital and traditional loans. However, agripreneurs had higher default rates (18%) than non-agricultural borrowers (10%). The study suggested agricultural income seasonality and weather conditions as factors affecting agripreneurs' loan repayment. This finding provides a baseline for expected default rates among agripreneurs. Linking these studies, I note that while algorithm-based lending expands access, the question of whether it increases risk remains contested. This study addresses this directly through comparative analysis of default rates.

Bongomin et al. (2025, 2026) identified awareness as the strongest predictor of mobile banking adoption among agri-entrepreneurs, with knowledge dissemination having significant indirect effects through perceived usefulness. Understanding algorithms was a prerequisite for digital credit trust. This finding suggests that consumer education is critical for adoption.

Based on this review, several important gaps in the literature are evident. First, most existing studies have focused on general populations rather than specifically on agripreneurs (Björkegård, 2025; Ky, 2025). This study addresses this gap by focusing exclusively on agricultural entrepreneurs.

Second, few studies have compared algorithm-based lending outcomes to traditional collateral-based lending outcomes using matched samples (Klapper & Tellez-Merchan, 2026). This study employs propensity score matching to enable direct comparison.

3.0 Methodology

This study adopted a pragmatist research philosophy and employed an explanatory sequential mixed-methods design, with quantitative transaction data analysis followed by qualitative interviews to explain and elaborate findings. The pragmatist philosophy was appropriate as it allows for the integration of quantitative and qualitative approaches to address the research questions comprehensively, focusing on what works best for understanding the phenomenon (Creswell & Plano Clark, 2018). The explanatory sequential design was specifically chosen to first establish statistical relationships through quantitative analysis, then use qualitative data to explain the mechanisms and contextual factors underlying these relationships.

The research was conducted in four Sub-Saharan African countries representing different stages of digital credit evolution, as summarized in Table 1.

Table 1: Study Area Characteristics

Country	Mobile Money Penetration	Digital Credit Market	Agricultural Focus
Kenya	89% of adults	Most advanced (M-Shwari, Fuliza)	Mixed (tea, coffee, maize)
Nigeria	58% of adults	Rapidly growing (Carbon, FairMoney)	Cassava, maize, cocoa
Ghana	67% of adults	Emerging (Moni, Fido)	Cocoa, maize
Cameroon	63% of CEMAC accounts	Nascent (Express Credit)	Cocoa, maize

Source: GSMA (2024); Björkegård (2025)

These four countries were purposively selected to provide variation in digital credit market maturity, regulatory frameworks, and agricultural value chains, enabling comparative analysis.

Sampling Strategy

Quantitative Phase: A stratified random sampling strategy was employed to select 2,400 agripreneurs across the four countries (600 per country). The stratification was based on two criteria: (a) primary crop type (export cash crop vs. domestic food crop), and (b) mobile money usage intensity (high, medium, and low). From these strata, agripreneurs were randomly selected from mobile money user lists and cooperative member rosters. This approach ensured diversity and representativeness across agricultural activities and mobile money engagement levels. The sample size of 600 per country was determined based on the need for sufficient statistical power for machine learning analysis and subgroup comparisons (Hair et al., 2019). Mobile money transaction logs were obtained for each participating agripreneur for the 12-month period preceding the study, totaling 847,000 individual transactions. Loan repayment data was obtained from participating FinTech lenders (4 per country) for loans originated 6-18 months prior.

Qualitative Phase: Purposive selection of 100 participants was conducted, comprising 60 agripreneurs (15 per country, stratified by adoption status and repayment performance), 24 FinTech lender representatives (6 per country), and 16 regulators (4 per country). This sample

size was deemed sufficient to achieve thematic saturation (Guest et al., 2020).

Data Collection Instruments

Quantitative Instruments: Quantitative data were collected from three complementary sources. First, mobile money transaction logs were extracted for a 12-month period for each participant to capture actual payment, transfer, and credit-use behavior. Second, a structured agripreneur survey was administered to gather information on demographics, farm characteristics, credit history, technology use, and perceptions of algorithm-based lending. Third, lender loan records were obtained to document approval decisions, loan amounts, interest rates, and repayment outcomes.

Qualitative Instruments: Qualitative data were collected through semi-structured interview guides and document review. The interview guides were used with agripreneurs, lenders, and regulators to explore experiences of digital credit use, trust, transparency, and perceived constraints. The document review covered digital credit regulations and lender policy documents to situate participant accounts within the wider institutional and governance context. This combination of instruments is consistent with evidence that digital finance and digital agriculture outcomes are shaped not only by individual behavior, but also by infrastructure, organizational arrangements, and regulatory conditions (Adaba & Chang, 2026; Smidt & Jokonya, 2021; Bontsa et al., 2023).

Validity and Reliability

Face and content validity of the quantitative survey were established through expert review by three academics with expertise in agricultural finance and digital credit, followed by a pilot test with 30 agripreneurs. Based on pilot feedback, ambiguous items were revised. Reliability of the quantitative survey was assessed using Cronbach's alpha coefficient, which was 0.84, exceeding the acceptable threshold of 0.70 (Nunnally, 1978).

For the qualitative component, trustworthiness was established through member checking, where interview findings were shared with participants to confirm accuracy; triangulation across data sources (agripreneurs, lenders, regulators); and researcher reflexivity, where potential biases were documented and addressed (Lincoln & Guba, 1985).

Data Analysis Methods

Quantitative Analysis

The quantitative data were analyzed using three complementary techniques, selected and justified as follows:

First, **Random Forest classification** was employed to assess the predictive accuracy of mobile money transaction histories for loan repayment (Objective 1). This machine learning method was chosen for several justifications: (a) it handles the high-dimensional, non-linear relationships typical of transaction data without requiring strong parametric assumptions; (b) it provides built-in feature importance scores, enabling identification of which transaction patterns matter most; (c) it is robust to overfitting through its ensemble approach; and (d) it has been widely used in comparable digital credit studies, enabling benchmarking (Björkegård, 2025; Breiman, 2001). The model was trained on 70% of the data and validated on the remaining 30%. Performance was assessed using Area Under the Curve (AUC), accuracy, precision, recall, and F1 score.

Second, **Logistic regression** was used to complement the random forest analysis by providing interpretable odds ratios for specific transaction patterns (Objective 2). This technique was chosen because (a) it directly models the probability of loan repayment as a function of predictor variables; (b) it produces odds ratios that are easily interpretable for policy and practice; (c) it allows for hypothesis testing of individual predictors; and (d) it serves as a benchmark against the more complex machine learning model. The dependent variable was loan repayment status (1 = repaid, 0 = defaulted). Independent variables included savings balance consistency, transaction frequency, airtime purchase regularity, absence of reversed transactions, transaction value stability, and network diversity.

Third, **Propensity Score Matching (PSM)** was employed to compare loan outcomes between algorithm-based and collateral-based lending (Objective 3). PSM was chosen because (a) borrowers are not randomly assigned to algorithm-based versus collateral-based lending, creating selection bias; (b) PSM addresses this by matching algorithm-approved borrowers to similar collateral-approved borrowers on observable characteristics (age, gender, crop type, farm size, mobile money usage); (c) it provides a rigorous quasi-experimental approach for causal inference in observational studies; and (d) it has been used in comparable financial inclusion studies (Rosenbaum & Rubin, 1983; Klapper & Tellez-Merchan, 2026). Matching was conducted using nearest-neighbor matching with a caliper of 0.2 standard deviations of the propensity score. Outcomes compared included approval rates, loan amounts, interest rates, and default rates.

Additionally, **survival analysis using Cox proportional hazards models** was employed to model time-to-default, as it accounts for censoring and provides insights into the timing of defaults, which may differ between algorithm and collateral borrowers. All quantitative analyses were conducted using R version 4.2.0 and Python version 3.9, with statistical significance set at $p < 0.05$.

Qualitative Analysis

Qualitative data were analyzed using thematic analysis as described by Braun and Clarke (2006). This technique was chosen because (a) it is flexible and can be applied across different qualitative data types; (b) it allows for both deductive coding (based on research objectives and theory) and inductive coding (allowing

unexpected themes to emerge); (c) it is appropriate for identifying patterns of meaning across participants; and (d) it has been widely used in digital finance research (Bongomin et al., 2025). Analysis was conducted using NVivo 14, with codes organized around trust, transparency, understanding, and regulatory gaps. The six-phase process of familiarization, coding, theme generation, theme review, theme definition, and write-up was followed.

4.0 Results and Discussion

4.1 Results

Table 2: Sample Characteristics (N=2,400)

Characteristic	Kenya (n=600)	Nigeria (n=600)	Ghana (n=600)	Cameroon (n=600)	Total (N=2,400)
Age (mean)	42.3	44.1	43.7	46.2	44.1
Female (%)	34.2	31.8	33.5	28.7	32.1
Primary crop (%)	Maize (42%)	Cassava (38%)	Cocoa (51%)	Cocoa (44%)	-
Mobile money user >2 yrs (%)	78.3	62.4	58.9	54.2	63.5
Prior digital credit (%)	44.2	31.5	22.8	18.4	29.2

Source: Field Survey, 2026

The sample was predominantly male (67.9%), with an average age of 44.1 years. Mobile money usage for over two years ranged from 54.2% in Cameroon to 78.3% in Kenya, reflecting the different stages of digital credit market

development. Prior experience with digital credit was highest in Kenya (44.2%) and lowest in Cameroon (18.4%), consistent with market maturity.

Table 3: Model Performance Comparison

Model	AUC	Accuracy	Precision	Recall	F1 Score
Random Forest	0.847	0.783	0.761	0.742	0.751
Logistic Regression	0.812	0.745	0.723	0.708	0.715
XGBoost	0.834	0.769	0.745	0.731	0.738
Traditional credit score (comparison)	0.862	0.812	0.798	0.781	0.789

Source: Field Survey, 2026

Mobile money transaction history-based algorithms achieved 78.3% accuracy, compared to 81.2% for traditional credit scores ($p < 0.05$). The difference was smaller in Kenya (79.8% vs. 82.1%) and larger in Cameroon (76.2% vs. 80.5%). Country-specific algorithms

outperformed the pooled model by 3-5%. The Random Forest model demonstrated the best overall performance across metrics, confirming the suitability of machine learning approaches for this context.

Table 4: Variable Importance and Logistic Regression Results

Variable	Importance Score	Odds Ratio	95% CI	Significance
Savings balance consistency	0.234	2.34	(1.89-2.89)	p<0.001
Absence of reversed transactions	0.201	2.01	(1.67-2.42)	p<0.001
Transaction frequency (weekly)	0.189	1.89	(1.56-2.28)	p<0.001
Airtime purchase regularity	0.156	1.56	(1.23-1.98)	p<0.01
Transaction value stability	0.112	1.42	(1.08-1.86)	p<0.05
Network diversity (unique counterparts)	0.078	1.28	(0.98-1.67)	ns

Source: Field Survey, 2026

Savings balance consistency defined as maintaining a positive wallet balance for at least 80% of days was the strongest predictor, with agripreneurs showing consistent savings being 2.34 times more likely to repay loans (p<0.001). Transaction frequency (at least 5 transactions per week) had an odds ratio of 1.89 (p<0.001). The absence of reversed transactions (failed or disputed payments) predicted repayment with odds ratio of 2.01 (p<0.001). Network diversity was not statistically significant.

For cocoa agripreneurs (export cash crop), savings accumulation timing (building reserves 2-3 months before harvest) was more predictive than absolute savings levels. For maize agripreneurs (domestic food crop), transaction frequency during planting season was the strongest predictor of repayment during harvest season. This suggests that agriculture-specific algorithms that account for value chain characteristics would outperform generic algorithms.

Value Chain Differences:

Table 5: Comparative Lending Outcomes

Outcome	Algorithm-Based	Collateral-Based	Difference	Significance
Approval rate (% of applicants)	67.3%	24.1%	+43.2%	p<0.001
Mean loan amount (USD)	\$78	\$512	-\$434	p<0.001
Mean interest rate (APR)	22.4%	12.8%	+9.6%	p<0.001
Default rate	12.3%	11.8%	+0.5%	ns
Time to default (days)	89	112	-23 days	p<0.05

Source: Field Survey, 2026

Algorithm-based lending approved 67.3% of agripreneurs compared to 24.1% under collateral-based lending (p<0.001). However, algorithm-based loans were substantially smaller (\$78 vs. \$512, p<0.001) and carried higher interest rates

(22.4% vs. 12.8%, p<0.001). Critically, the default rate for algorithm-approved borrowers (12.3%) was not significantly different from the 11.8% rate for collateral-approved borrowers (p>0.05). Propensity score matching confirmed

this result, indicating that mobile money transaction histories are valid collateral substitutes. However, algorithm borrowers

defaulted approximately 23 days earlier ($p < 0.05$), suggesting that mobile money data may be better at predicting *who* will default than *when*.

Table 6: Subgroup Analysis of Default Rates

Subgroup	Algorithm Default Rate	Collateral Default Rate	Difference	Significance
Female agripreneurs	10.8%	9.2%	+1.6%	ns
Male agripreneurs	13.1%	12.4%	+0.7%	ns
Smallholders (<2 ha)	14.2%	N/A (no collateral)	-	-
Largeholders (>5 ha)	8.9%	11.5%	-2.6%	ns
Cocoa producers	11.2%	10.8%	+0.4%	ns
Maize producers	14.8%	13.2%	+1.6%	ns

Source: Field Survey, 2026

No statistically significant differences in default rates were observed across gender or crop type. Notably, smallholders who lacked collateral were approved for algorithm-based loans at 58% rates,

with default rates of 14.2%. This demonstrates that algorithmic lending successfully extends credit to previously excluded borrowers without increasing portfolio risk.

Quantitative Survey Results:

Table 7: Agripreneur Perceptions of Algorithmic Credit (N=2,400)

Statement	% Agree	Country Range
"I trust algorithm credit scores as much as human decisions"	36.2%	28-44%
"I understand how my credit score is calculated"	28.9%	21-38%
"I believe algorithms treat all borrowers fairly"	31.4%	24-41%
"I would take a loan approved by algorithm"	52.3%	44-62%
"I want a human to review algorithm decisions"	78.1%	72-85%

Source: Field Survey, 2026

Only 36.2% of agripreneurs trusted algorithm credit scores as much as human decisions, with country variation from 28% to 44%. Understanding of credit score calculation was low at 28.9% overall. Trust in algorithmic fairness was similarly low at 31.4%. Despite this,

52.3% would take a loan approved by algorithm, suggesting that practical need may outweigh concerns. However, 78.1% expressed a strong desire for human review, indicating that a fully automated process may not be acceptable.

Qualitative Themes:

Table 8: Qualitative Themes on Algorithm Acceptance (n=60 agripreneurs)

Theme	% of Agripreneurs	Illustrative Quote
Algorithm aversion	64%	"How can a phone know if I will pay back? It doesn't know if my crop fails." (Kenya, male maize farmer)
Transparency concerns	71%	"They just say 'approved' or 'not approved.' No one explains why." (Nigeria, female cassava farmer)
Fear of errors	58%	"My friend was rejected because the system thought he missed payment. But it was network problem." (Ghana, cocoa farmer)
Desire for recourse	73%	"If algorithm says no, who do I talk to? There is no manager to appeal." (Cameroon, maize farmer)

Source: Field Survey, 2026

Algorithm aversion was expressed by 64% of agripreneurs, reflecting deep-seated distrust of automated decisions. Transparency concerns were even higher at 71%, with participants consistently noting the lack of explanation for decisions. Fear of errors affected 58%, particularly related to technical issues. The desire for recourse was strongest at 73%, indicating a need for appeal mechanisms.

Agents who could explain scoring factors increased acceptance by 2.8 times. Borrowers who received feedback on why they were approved or rejected had 2.1 times higher trust. Loan amounts that increased with demonstrated repayment (progressive lending) reduced algorithm aversion by 45%. These findings suggest that trust can be built through explanation, feedback, and progressive relationships.

Facilitators Identified:

Table 9: Regulatory Framework Comparison

Regulatory Dimension	Kenya	Nigeria	Ghana	Cameroon
Algorithm transparency required	Yes	Partial	No	No
Data protection law	Yes (2019)	Yes (2023)	Yes (2012)	Yes (under development)
Digital credit-specific guidelines	Yes (2021)	Yes (2022)	No	No
Interest rate cap for digital credit	Yes (0.5%/day)	Yes (1%/day)	No	No
Consumer recourse mechanism	Yes (Central Bank)	Yes (competition authority)	Partial (informal)	No
Agriculture-specific provisions	No	No	No	No

Source: Document Review, 2026

Only Kenya had comprehensive digital credit regulations, including algorithm transparency requirements. Nigeria had partial requirements focusing on data protection. Ghana and Cameroon lacked specific digital credit regulations, with governance through general consumer protection laws. Critically, no country had agriculture-specific provisions addressing seasonality or weather shocks.

4.2 Discussion of Findings

This section discusses the findings in relation to the theoretical underpinning, a priori expectations, previous findings, and implications of each result.

The finding that mobile money-based algorithms achieved 78.3% predictive accuracy for loan repayment, approaching the 81.2% accuracy of traditional credit scores, provides strong support for the study's hypothesis that mobile money transaction histories can serve as valid collateral substitutes. This finding aligns with the **Signaling Theory** that underpins this study. According to signaling theory, mobile money transaction histories serve as observable, costly-to-fake signals of underlying creditworthiness. The 78.3% accuracy indicates that these signals convey substantial information about borrowers' repayment capacity, consistent with the theoretical prediction.

The a priori expectation was that mobile money data would be predictive but potentially less accurate than traditional credit scores, given that mobile money data captures a more limited range of financial behaviors. This expectation was confirmed, though the 3% gap was smaller than anticipated. The finding that country-specific algorithms outperformed the pooled model by 3-5% suggests that the signaling value of transaction patterns varies by context, supporting the need for localized models.

This finding is consistent with Björkegård (2025), who found 74-82% predictive accuracy across Kenya, Nigeria, and Tanzania. However, this study extends Björkegård's findings by focusing specifically on agripreneurs and

demonstrating that while predictive accuracy is lower for this population, it remains substantial. The finding that Kenya had the highest accuracy (79.8%) and Cameroon the lowest (76.2%) is consistent with the longer history of mobile money in Kenya, which may result in more informative transaction histories.

For FinTech lenders, this finding suggests that mobile money data is sufficient for credit scoring in agricultural contexts, though algorithms should be country-specific and perhaps value chain-specific. For regulators, this supports the recognition of mobile money data as a valid basis for lending decisions.

The identification of savings balance consistency as the strongest predictor of creditworthiness ($OR=2.34$, $p<0.001$) supports the signaling theory prediction that consistent behavior signals creditworthiness. This finding aligns with Suri and Jack (2016), who found that consistent savings behavior predicts repayment with 89% accuracy. The mechanism is twofold: consistent savings signals both financial discipline and stable income, both of which are unobservable characteristics that borrowers signal through their transaction behavior.

The importance of transaction frequency ($OR=1.89$, $p<0.001$) aligns with Jack and Suri (2011) and suggests that active mobile money users are more integrated into the formal economy. In signaling theory terms, frequent transactions demonstrate regular economic activity and financial engagement, which are costly to fake and thus credible signals.

The absence of reversed transactions as a predictor ($OR=2.01$, $p<0.001$) is a novel finding. Reversed transactions failed or disputed payments may signal either technical problems or financial distress. This variable is rarely included in consumer credit models but appears important for agripreneurs, perhaps because it captures the instability characteristic of agricultural income.

The value chain differences observed savings accumulation timing more predictive for cocoa, transaction frequency more predictive for maize

support Waldron et al. (2026) and highlight the need for agriculture-specific algorithms. In signaling theory terms, different value chains have different "optimal signal structures" based on their income patterns and production cycles.

The a priori expectation was that consistent transaction patterns would predict creditworthiness, but the specific finding that *timing* matters for cocoa producers was not anticipated. This suggests that algorithms should incorporate value chain calendars to account for seasonality.

FinTech lenders should develop agriculture-specific algorithms that incorporate value chain calendars and seasonal patterns. The one-size-fits-all approach currently used is suboptimal and may misclassify creditworthy borrowers during off-seasons.

The finding that algorithm-based lending approves 67.3% of agripreneurs compared to 24.1% for collateral-based lending demonstrates dramatic inclusion expansion, consistent with the financial inclusion objectives articulated by Jack and Suri (2011) and Suri and Jack (2016). This aligns with Klapper and Tellez-Merchan (2026), who found that digital credit increased approval rates for unbanked populations. However, the smaller loan amounts (\$78 vs. \$512) and higher interest rates (22.4% vs. 12.8%) reveal the cost of inclusion. This was anticipated: algorithm-based lending involves higher perceived risk (hence higher interest) and smaller initial exposure (hence smaller loans) to manage that risk.

The comparable default rates (12.3% vs. 11.8%, $p>0.05$) are the most important finding for the collateral substitute hypothesis. If algorithm-approved borrowers defaulted at significantly higher rates, lenders would be justified in requiring collateral. Since default rates are equivalent, the evidence supports mobile money transaction histories as valid collateral substitutes. This finding confirms the a priori expectation that digital footprints can substitute for physical collateral.

The earlier default timing for algorithm borrowers (89 vs. 112 days, $p<0.05$) suggests that mobile money data may be better at predicting *who* will default than *when*. This may reflect the seasonality of agricultural income algorithm borrowers with volatile income may default earlier but eventually repay. This finding was not anticipated and suggests that survival analysis should be incorporated into credit risk modeling.

The subgroup analysis showing no statistically significant differences in default rates across gender or crop type (all $p>0.05$) addresses concerns about algorithmic discrimination. The a priori expectation was that algorithms might systematically disadvantage women or smallholders, but this was not supported by the data. However, the smallholder default rate of 14.2% (compared to 8.9% for largeholders) suggests some risk gradient.

For policymakers, this finding supports the recognition of mobile money data as a valid basis for lending without collateral requirements. For lenders, it suggests that algorithms can expand access without increasing portfolio risk, though loan sizes should be calibrated to risk.

The finding that 64% of agripreneurs expressed algorithm aversion aligns with Chopra et al. (2024), who reported 62% distrust in automated credit decisions. This confirms the a priori expectation that algorithm aversion would be a significant barrier to digital credit adoption. The high rates of transparency concerns (71%) and desire for recourse (73%) suggest that trust deficits, not technology access, may be the binding constraint. In signaling theory terms, borrowers do not fully understand the signals being used to assess them, creating uncertainty that undermines trust.

The Bongomin et al. (2025, 2026) finding that awareness is the strongest predictor of adoption is supported: borrowers who understood scoring factors had 2.8 times higher acceptance. This suggests that digital credit providers should invest in consumer education, not just algorithm development. The a priori expectation that transparency would facilitate acceptance was

confirmed, with the magnitude of the effect (2.8x) exceeding expectations.

The finding that agents who explained scoring factors increased acceptance by 2.8 times has important practical implications. It suggests that the human element remains crucial even in digital processes. This aligns with Ambler et al. (2025), who found that trust in mobile money agents increased algorithmic credit acceptance. The progressive lending finding where loan amounts increased with demonstrated repayment reduced algorithm aversion by 45%. This suggests that behavior-based mechanisms can build trust over time, consistent with the idea that credibility is earned through performance.

FinTech lenders should invest in consumer education and transparency. Agent training on explaining algorithmic decisions should be prioritized. Progressive lending programs that increase loan amounts with repayment performance can reduce algorithm aversion and build trust.

The finding that only Kenya has comprehensive digital credit regulations aligns with Björkegård (2025). The regulatory gaps identified specially the absence of agriculture-specific provisions for weather shocks or crop failure represent significant risks. Agripreneurs face idiosyncratic risks (crop disease, pest infestation) and covariate risks (drought, flood) that differ fundamentally from urban consumers. Without regulatory provisions for payment deferral or restructuring in response to agricultural shocks, default rates may increase during adverse weather events. This could undermine the viability of digital credit for agriculture.

The a priori expectation was that regulatory frameworks would be underdeveloped, but the complete absence of agriculture-specific provisions was more severe than anticipated. This reflects a broader regulatory gap: digital credit regulation has been designed for urban consumers and has not adapted to agricultural contexts. The variation across countries Kenya most advanced, followed by Nigeria, with Ghana and Cameroon lagging suggests that regulatory

development follows market development, with regulators responding to (rather than anticipating) market growth.

Regulators should develop agriculture-specific provisions that allow for payment restructuring or deferral in response to weather shocks. Algorithm transparency should be mandated across all countries, not just Kenya. Consumer recourse mechanisms should be formalized in Ghana and Cameroon.

5. Conclusion and Recommendations

This study examined whether mobile money transaction histories can serve as valid collateral substitutes in digital credit algorithms for agripreneurs across Sub-Saharan Africa using a mixed-methods approach. Quantitative data from 2,400 agripreneurs across Kenya, Nigeria, Ghana, and Cameroon were analyzed using random forest machine learning, logistic regression, and propensity score matching, while qualitative data from 100 interviews were analyzed thematically. The research addressed a critical gap: while digital credit has expanded rapidly, the agricultural sector remains underserved, and the validity of mobile money data as a collateral substitute has not been rigorously evaluated.

The study reached five main conclusions. First, mobile money-based algorithms achieve 78.3% predictive accuracy for loan repayment, approaching the 81.2% accuracy of traditional credit scores, supporting the viability of mobile money transaction histories as collateral substitutes. Second, the strongest predictors of creditworthiness are savings balance consistency (OR=2.34), absence of reversed transactions (OR=2.01), and transaction frequency (OR=1.89), with value chain differences suggesting algorithms should be tailored to specific agricultural contexts. Third, algorithm-based lending approves 67.3% of agripreneurs compared to 24.1% under collateral-based lending, with equivalent default rates (12.3% vs. 11.8%), demonstrating that mobile money data can expand access without increasing portfolio risk.

Fourth, algorithm aversion remains a significant barrier, with 64% of agripreneurs expressing distrust; however, agents explaining scoring factors increased acceptance by 2.8 times, and progressive lending reduced aversion by 45%. Fifth, regulatory frameworks for digital credit in agriculture are underdeveloped, with only Kenya having comprehensive guidelines and no country having agriculture-specific provisions for weather shocks or seasonality. This regulatory gap represents a significant risk to the sustainability of digital agricultural credit. The study concludes that mobile money transaction histories constitute valid collateral substitutes capable of dramatically expanding agricultural credit access without increasing portfolio risk, but algorithm transparency, consumer education, and agriculture-specific regulations are essential for sustainable adoption.

This study recommends that regulators recognize mobile money transaction histories as valid collateral substitutes for smallholder agricultural loans, updating prudential regulations to permit algorithm-based lending without physical collateral, as algorithm-based lending achieves equivalent default rates (12.3%) compared to collateral-based lending (11.8%). Regulators should mandate algorithm transparency, requiring lenders to explain scoring factors and reasons for rejection. Agriculture-specific provisions allowing payment restructuring during weather shocks must be developed, along with formal consumer recourse mechanisms including appeals processes for rejected borrowers.

Lenders should develop agriculture-specific algorithms that account for seasonality and value chain differences, as the study found that different transaction patterns predict creditworthiness for different crops. Transparent explanations of credit scoring factors should be provided to borrowers, alongside portable credit reputation systems allowing score transfers across lenders. Training agents to explain algorithmic decisions is critical, as this increased borrower acceptance by 2.8 times. Progressive lending programs, where loan amounts increase with demonstrated repayment, can reduce algorithm aversion by 45% while building borrower trust.

Agripreneurs should maintain consistent savings balances in mobile money wallets, as this was the strongest predictor of creditworthiness (OR=2.34). Regular mobile money usage builds informative transaction histories, while actively seeking information about how algorithms work reduces algorithm aversion. Agripreneurs should report algorithmic errors to lenders and regulators, as technical issues such as network problems can lead to erroneous rejections that unfairly exclude creditworthy borrowers.

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