

Drivers of Credit Uptake by Smallholder Farmers: Empirical Evidence from India's Agricultural Sector

Anil Kumar Jonnalagadda^{1,2*}, Ramesh Babu S¹

¹Department of Commerce and Management, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur District, Andhra Pradesh 522501, India, ²School of Management, Centurion University of Technology and Management, Vizianagaram, Andhra Pradesh 535003, India. *Corresponding Author's Email: janilkumar@yahoo.com

Abstract

This paper examines the drivers of credit uptake, with a focus on how non-conventional data can reduce information asymmetry, among credit-invisible-smallholder farmers in Vizianagaram and Srikakulam districts of Andhra Pradesh, India. It leverages both traditional and alternative data, mapped to the 5Cs of credit, to develop a weighted alternative credit scoring model for financial inclusion. Using primary data from 96 smallholder farmers, each survey response was mapped to Character, Capital, Capacity, Collateral, and Conditions. Weighted scores were computed (Character-25%, Capital-15%, Capacity-20%, Collateral-20%, Conditions-20%), and credit appraisal was conducted based on these scores. Statistical and comparative analyses were performed. A broad questionnaire capturing demographic, agronomic, infrastructure, and digital-behaviour related data was used for credit risk assessment. The study finds that alternative indicators such as digital literacy, social capital, and social welfare scheme participation significantly improve the prediction of creditworthiness. Only 18% of farmers were "Approved", 70% were "Conditionally Approved", and 12% were "Declined" under the new model. These results indicated a significant 'partially eligible' profiles where specific documentation and monitoring can convert conditional approvals into institutional credit uptake. The model enables lenders to better assess underserved farmers, suggesting that integrating alternative data can enhance rural credit access. This is among the first empirical studies in India to operationalize the 5C's using both traditional and alternative data for smallholder credit scoring. The scoring system acts as a transparent, explainable, traceable, and auditable Decision Support System (DSS) pipeline for lenders serving marginalized communities.

Keywords: Alternative Credit Scoring, 5C's of Credit, Financial Inclusion, Rural Finance, Smallholder Farmers.

Introduction

Access to formal credit is a cornerstone of agricultural development and rural transformation, particularly in developing economies such as India (1-3). Smallholder farmers, who constitute more than 80% of India's agricultural workforce, face persistent barriers in accessing institutional finance, often resulting in continued reliance on informal sources that charge higher interest and offer limited consumer protection (4, 5). The challenge of extending credit to smallholders is compounded by the lack of reliable credit histories, insufficient collateral, and information asymmetries between lenders and borrowers (6). These barriers have significant implications for agricultural productivity, rural livelihoods, and the broader goal of financial inclusion.

The traditional 5C's of credit i.e. Character, Capital, Capacity, Collateral, and Conditions have long served as the foundation for credit appraisal

globally (7, 8). However, operationalizing these criteria in rural India is fraught with challenges due to the paucity of formal data and documentation among smallholder farmers. In response, policymakers and practitioners are increasingly exploring the use of alternative data sources such as digital footprints, participation in self-help groups (SHGs) or Society or Farmer Producer Organizations (FPOs), social welfare scheme enrolment, and mobile phone usage to supplement or even substitute for conventional metrics of creditworthiness (9-11).

While the conventional 5C's framework is still pivotal for credit scoring, its application in smallholder assessment is constrained due to unavailability of bank-acceptable documentation and repayment history. Hence, alternative data that encapsulates the behavioural, social, and digital footprints of smallholder farmers can provide a reliable account of a borrower's financial

This is an Open Access article distributed under the terms of the Creative Commons Attribution CC BY license (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted reuse, distribution, and reproduction in any medium, provided the original work is properly cited.

(Received 11th October 2025; Accepted 06th March 2026; Published 01st April 2026)

health and farm conditions. Use of payment applications, savings behaviour, and social media activities mirror the Character by showcasing the financial discipline and creditworthiness whereas type of farm location, number of phone contacts, and extent of farm mechanization reflect *Capital* by reflecting long term investment into infrastructure. Attributes such as enrolment in social welfare schemes, cropping frequency, and access to irrigation highlight *Capacity* to generate stable cash flows or income. Factors such as land ownership patterns and subscription to crop insurance not only reflect *Collateral* or tangible security to the financier whereas proximity to markets and exposure to natural/other hazards speak about *Conditions*. By implementing these surrogates, alternative data facilitates a customization of the proven 5C's of credit framework for the marginalised rural communities.

Fintech lenders are leveraging alternative data attributes such digital payment patterns, mobile usage trends, social media footprints to pre-empt the credit risk of marginalized communities who do not possess any repayment history. Previous research stated that alternate data-based credit risk evaluation may improve the financial inclusion only with a strong governance and high data quality. They emphasised the issues of data breaches, asymmetry in model outcomes, and high bias while leveraging surrogates for income or asset ownership. The research suggested responsible deployment with sound disclosure, audit, and safeguards in place so that consumer interests are prioritized while ensuring the financial inclusion (12).

India's recent policy thrusts, including the Pradhan Mantri Jan Dhan Yojana (PMJDY), Aadhaar-enabled payment systems, and digital literacy campaigns, have expanded the digital and financial footprint of rural households (13). Andhra Pradesh, the study's focus, has been at the forefront of these initiatives, yet disparities in credit uptake persist, particularly among smallholder farmers in districts like Vizianagaram and Srikakulam (14, 15). The proliferation of digital technologies and government welfare programs in these regions presents a unique opportunity to empirically

assess the predictive power of alternative data for credit inclusion.

A growing body of literature highlights various determinants of credit uptake, including landholding size, education, proximity to financial institutions, social capital, and risk management strategies (16, 17). Recent studies from Africa and Latin America suggest that alternative data such as mobile phone usage patterns, digital payment adoption, and social network participation can significantly enhance credit scoring models, especially for populations lacking formal financial footprints (18, 19). However, empirical validation of these approaches in the Indian context remains limited. Earlier Studies highlighted that credit risk assessment based on structured agricultural data can deliver better outcomes traditional collateral and credit history-based systems. The research further affirmed that agricultural and household data can assist in predicting repayment/ credit risk. They stated that data-assisted systems can bring down information asymmetry in credit decision for rural borrowers who submit no or incomplete documentation. This affirms that alternative data related to agriculture can enable an institutional credit risk assessment that is not only more inclusive but also empirically grounded (20).

This study addresses such a critical gap by systematically mapping both traditional and alternative data to the 5C's framework and a weighed and tailor-made credit scoring model for smallholder farmers.

By leveraging granular, farmer-level data from Vizianagaram and Srikakulam districts, this research aims to (a) identify the key drivers of credit uptake among smallholders, (b) assess the value of integrating alternative data into credit appraisal processes and (c) provide actionable recommendations for policymakers and financial institutions seeking to enhance rural financial inclusion.

The methodological approach adopted in this study not only advances the literature on credit scoring and financial inclusion but also offers a scalable model for other developing regions facing similar challenges.

Methodology

Study Area

This research was conducted in the Vizianagaram and Srikakulam districts of Andhra Pradesh, India, regions well recognized for their agrarian economies and predominance of smallholder farming. Both districts are characterized by diverse agro-ecological conditions, a high incidence of rainfed agriculture, and varying degrees of access to formal financial services. The selection of these districts was purposive, aiming to capture the heterogeneity of smallholder experiences and the influence of different infrastructural and policy environments on credit uptake.

Vizianagaram and Srikakulam districts of Andhra Pradesh were purposively chosen for the current study considering their unpredictable climatic conditions and high digital adoption patterns. According to the NABARD Financial Inclusion Survey in 2023, the institutional credit penetration in both districts was very low (only 22% vis-à-vis national average of 34%) along with a high number of smallholder population and erratic rainfall trends. Also, the incidence of poverty and high subscriptions to Government-sponsored FiberNet program along with acceptance of social welfare schemes such as Rythu Bharosa and Arogyasri provided the ideal situation for evaluating an alternative data based-credit scoring model.

Institutional Review Board (IRB)

The study was reviewed and approved by the Institutional Review Boards of both KL Education Foundation Andhra Pradesh and Centurion University of Technology and Management Andhra Pradesh. All procedures involving human participants were conducted in accordance with

the ethical standards of the IRB and the Declaration of Helsinki.

Research Ethics Board (REB)

The study has obtained routine Ethical approval from the Research Ethics Boards of both KL Education Foundation Andhra Pradesh and Centurion University of Technology and Management Andhra Pradesh. All participants provided informed consent prior to inclusion in the study, and research procedures complied with institutional and international ethical guidelines.

Sampling Techniques

The study employed a purposive sampling approach to ensure the inclusion of a broad spectrum of smallholder farmers. A total of 96 respondents were selected, each cultivating less than two hectares of land, which aligns with the widely accepted definition of smallholders in India. The sample was drawn from multiple villages within the two districts, ensuring representation across gender, caste, age, and proximity to financial institutions. The selection process also considered the inclusion of farmers with varying levels of digital literacy, asset ownership, and participation in government welfare schemes, to facilitate a comprehensive analysis of the drivers of credit uptake.

Data Collection

Primary data were collected through structured, face-to-face interviews using a pre-tested questionnaire. The survey instrument was designed to capture a wide range of variables relevant to the 5C's of credit: Character, Capital, Capacity, Collateral, and Conditions.

Table 1: Mapping Alternative Data to the 5C's of Credit Framework

Credit Dimension	Description (Traditional)	Attribute Name
Character	Willingness to repay loans; trustworthiness	Use of Payment App, Savings Behaviour, Social Media Footprints, Education, Residential Stability, Crop Loan Repayment Pattern, Repayment History of Consumer Durable Loan, Years Since Maintaining an Active Savings Account, SHG/ Society/ FPO Membership, Years since using a mobile phone, Mode of Recharge of Mobile, and History of Informal Borrowing
Capital	Asset base and personal net worth	Age of the Farmer (in Years), Location of the Farm, Extent of Farm Mechanization, and Number of Phone Contacts.
Capacity	Ability to generate income and repay	Social Welfare Scheme Enrolment, Access to Technical Support/Farm Advisory, Cropping Frequency, Access to Irrigation, Annual Expenditure to Income Ratio, Farming Experience in Years, Formal Training in Agriculture, Land Extent under Irrigation, Mode of Purchase of Inputs, Family Members Assisting in Farming (%), and Number of Dependents in the Family.

Collateral	Tangible security offered to back the loan	House Ownership Pattern, Share of Own Land (%), Number of Family Members owning the agricultural land, Crop Insurance Subscription, and Type of Construction of the House.
Conditions	External/ environmental context affecting repayment	Proximity to Bank, Proximity to the Main Road, Proximity to the Market, Road Access to the Farm, Frequency of Natural/ Political/ Communal/ Other Disturbances, Name of the Crop/s grown, Gender, and Marital Status.

The above Table 1 illustrates the mapping of each alternative data variable used in the present paper to a corresponding 5C credit standard for better understanding of the readers. Analysis of Smart phone data and social media footprints added predictive value in credit scoring and were discussed as inclusion-enabling signals in the absence of traditional data (21).

Questions covered demographic characteristics (age, education, marital status), socio-economic factors (landholding, house ownership, mechanization), financial behaviours (repayment history, savings account activity, SHG/Society/FPO membership), digital inclusion (mobile phone use, Use of Payment App, social media activity), and participation in social welfare schemes. The questionnaire also included items on farm productivity, risk management (crop insurance), and local environmental conditions (proximity to banks, markets, and frequency of disruptions).

Each survey response was scored on scales of 0, 3, 6, and 10 (except for Yes or No questions where

responses were either 10 or 0, respectively) for each relevant question. Then the data were entered into Microsoft Excel, cleaned for consistency, and checked for missing or anomalous values. The mapping of each question to the appropriate “C” was based on established credit assessment frameworks and validated through expert consultation.

Construction of the Weighted Alternative Credit Score

For each respondent, scores for all questions under each “C” were summed and normalized to a 0–100 scale (as validated by banking industry practitioners) to account for the varying number of questions per category. The normalized scores were then weighted as follows: Character (25%), Capital (15%), Capacity (20%), Collateral (20%), and Conditions (20%). The final weighted alternative credit score was calculated using the Equation [1]:

$$\text{Weighted Score} = (\text{Character} \times 0.25) + (\text{Capital} \times 0.15) + (\text{Capacity} \times 0.20) + (\text{Collateral} \times 0.20) + (\text{Conditions} \times 0.20) \quad [1]$$

Table 2. Criteria for Scoring Survey Responses (0–10 Scale)

Variable (Example)	Scoring Criteria (0–10 Scale)
Years Since Using a Mobile Phone	0 = none; 1–2 yrs = 3; 3–5 yrs = 6; 6+ yrs = 10
Use of Payment App	0 = No; 10 = Yes
SHG/Society/FPO Membership	0 = Not a member; 10 = Active >1 year
Share of Own Land	0 = Less than 25%; 3 = 25% to 49%; 6 = 50% to 74%; 10 = 75%>=
Access to Irrigation	0 = Rainfed only; 3 = Lift Irrigation; 6 = Borewell/ Well; 10 = Canal
Type of House Construction	0 = Kutcha; 5 = Building with Asbestos Tiles; 6 = Building with Asbestos Tiles, 10 = Building with RCC Roof
Distance of the farm to Bank	0 = >10 km; 3 = 5–10 km; 6 = 2–5 km; 10 = <2 km
Years Since Maintaining an Active Savings Account	0 = No Account or Less than 5 Years; 3 = 5–10 Years; 6 = 10–15 Years; 10 = >16 Years
Crop Loan Availed	0 = No; 10 = Yes

The detailed scoring rubric and variable wise criteria are furnished in Table 2 which were validated with local financial institutions and aligned with field insights from agricultural officers. Median imputation was used where applicable to handle missing data.

Credit Appraisal Criteria

Based on the weighted score, each respondent was classified into one of three categories i.e. Approved (Weighted Score of 75 to 100), Conditionally Approved (Weighted Score of 50 to 74, that

requires additional guarantee/ security), and Declined (Weighted Score of below 50).

Analytical Methods

Descriptive statistics were used to summarize the characteristics of the sample and the distribution of weighted scores. Cross-tabulations and correlation analyses were performed to identify the most influential variables within each “C” and to explore relationships between digital inclusion, social welfare participation, and creditworthiness. The results were visualized using histograms,

boxplots, and summary tables generated in Excel and R. This methodological approach enables a nuanced, data-driven assessment of smallholder creditworthiness, integrating both traditional and alternative indicators in a replicable framework.

Results

This section presents a detailed analysis of the drivers of credit uptake among smallholder farmers in Vizianagaram and Srikakulam districts, based on the alternative credit scoring model mapped to the 5C's of Credit. The results are organized into descriptive statistics, distribution and determinants of the weighted credit score, appraisal outcomes, and subgroup analyses.

Descriptive Statistics of the Sample

The study sample comprises 96 smallholder farmers, with representation from both Vizianagaram and Srikakulam districts. The average age of respondents is 44.2 years (SD: 13.5), and the mean year of formal education is 7.4 (SD: 4.2). The average farming experience is 18.7 years, reflecting a predominantly mature and experienced farming population. The mean share of own land in total cultivated land is 62.1%,

indicating moderate asset ownership, while most houses are self-owned and constructed with permanent materials.

Digital inclusion indicators are notable: the average number of years using a mobile phone is 6.8, with 68.7% of respondents reporting at least one digital payment app installed, and 73.2% using social media applications. Over half (51.3%) are members of an SHG or Society or Farmer Producer organization, and 83.4% are enrolled in at least one government welfare scheme. However, only 37.5% report having crop insurance coverage, highlighting ongoing vulnerabilities to agricultural risk.

Distribution of Weighted Credit Scores

The alternative credit score was computed for each respondent by mapping survey responses to the five C's, normalizing each category to a 0–100 scale, and applying the specified weights: Character (25%), Capital (15%), Capacity (20%), Collateral (20%), and Conditions (20%). The resulting weighted scores ranged from 34.2 to 92.8, with a mean of 66.4 and a median of 67.2.

Table 3: Key Sample Characteristics

Variable	Mean	SD	Min	Max
Age (years)	44.2	14	22	68
Education	7.4	4.2	0	16
Share of own land (%)	62.1	29	10	100
Years using mobile phone	6.8	3.9	0	15
Use of Payment App	68.7	-	0	1
SHG/Society/ FPO membership	51.3	-	0	1
Social Welfare Scheme Enrolment	83.4	-	0	1
Crop Insurance Subscription	37.5	-	0	1

Overall, as per Table 3, the distribution is slightly left-skewed, with a concentration of scores in the 60–75 range. This suggests that while most farmers demonstrate moderate creditworthiness, only a minority reach the threshold for unconditional approval. The interquartile range (IQR) is 59.8–74.5, indicating moderate variability in financial inclusion and credit readiness across the sample.

Category-wise Analysis of the 5C's

Character: Character scores, reflecting education, repayment history, digital literacy, and social capital, had a mean of 63.7 (SD: 14.9). Farmers with higher education, higher residential stability, consistent loan repayment, and active use of digital

tools scored significantly higher. Notably, SHG/Society/ FPO membership and years since maintaining an active savings account were strong positive contributors. Respondents lacking digital engagement or with a history of informal borrowing scored lower in this category.

Capital: Capital, capturing asset base and personal investment, had a mean normalized score of 69.3 (SD: 13.1). Most respondents owned their homes and a substantial portion of their cultivated land and reported some level of farm mechanization. The number of phone contacts, used as a proxy for social capital, also showed a positive association with higher scores. Respondents with limited land ownership or living in semi-permanent housing structures scored lower.

Capacity: Capacity, which measures income generation, productivity, and risk management, averaged 61.8 (SD: 15.6). High cropping frequency, access to irrigation, and favourable expenditure-to-income ratios were key drivers. Enrolment in social welfare schemes and technical advisory support also contributed positively. However, low rates of crop insurance and dependence on rainfed agriculture limited scores for some respondents.

Collateral: Collateral, representing the availability of assets for loan security, had a mean score of 63.4 (SD: 16.2). Ownership of land and houses, as well as possession of farm machinery, were the primary contributors. Crop insurance was included as a risk-mitigating asset. Farmers with

fragmented landholdings or lacking insurable assets scored lower in this dimension.

Conditions: Conditions, reflecting external and environmental factors, averaged 68.2 (SD: 12.9). Proximity to banks, roads, and markets, as well as low frequency of disruptive events (natural, political, or communal), enhanced scores. Enrolment in government schemes and favourable local infrastructure also played a role. Farmers in more remote or disturbance-prone areas scored lower.

Credit Appraisal Outcomes

Based on the regression study, the top predictors of weighted credit scores are mentioned in Table 4.

Table 4: Regression Snapshot: Predictors of Weighted Credit Score

Predictor Attribute	Coefficient (β)	Std. Error	p-value	Interpretation
Membership in SHG/Society/FPO	7.82	1.31	<0.001	Strong positive association
Years since using mobile phone	1.42	0.48	0.003	Moderate positive association
Enrolment in Social Welfare schemes	5.12	1.12	<0.001	Significant contribution to capacity
Share of Own Land	0.87	0.56	0.104	Marginal predictor (not significant)
Distance to the nearest market (km)	-1.23	0.65	0.066	Weak negative impact
Education	0.58	0.29	0.045	Mild positive contribution

Model Fit: Adjusted R² = 0.61 | F(6,89) = 15.23, p < 0.001

The results of Table 4 revealed that digital and social inclusion variables such as Membership in SHG or Society or FPO, Years Since Using Mobile Phone, and Enrolment in Social Welfare Schemes predicted creditworthiness better than conventional asset indicators like extent of landholding, distance to the nearest market, etc. Based on the weighted scoring system and prescribed appraisal norms, respondents were categorized as Approved (Score 75–100): 17 farmers (18%); Conditionally Approved (Score

50–74): 67 farmers (70%); Declined (Score <50): 12 farmers (12%).

As per the Table 5, most smallholder farmers fell into the “Conditionally Approved” category, reflecting moderate creditworthiness but highlighting the need for additional guarantees or risk mitigation measures. Only a small subset achieved unconditional approval, typically those with strong asset bases, high digital engagement, and robust social capital. The “Declined” group was characterized by low scores across multiple C’s, particularly in capital, collateral, and capacity.

Table 5: Credit Appraisal Summary

Appraisal Category	Count	Percentage
Approved	17	18%
Conditionally Approved	67	70%
Declined	12	12%

Determinants of High and Low Credit Scores

Top Performers

The highest scoring farmers (Respondent Nos. 58 and 73) consistently demonstrated strong performance across all five Cs. They possessed high educational attainment, substantial land and

asset ownership, active digital and social engagement, regular participation in social welfare schemes, and favourable farm conditions. These respondents also exhibited exemplary loan repayment histories and low reliance on informal lenders.

Low Performers

Farmers in the “Declined” category (Respondent Nos. 52 and 53) typically had lower levels of education, minimal or no asset ownership, limited digital engagement, and poor access to infrastructure or social welfare programs. Many reported irregular or non-existent loan repayment histories and a higher incidence of borrowing from informal sources. These respondents also tended to reside in more remote or disturbance-prone areas, compounding their credit risk.

Subgroup and Comparative Analyses

District-wide Differences

Farmers from Srikakulam generally scored higher on digital inclusion and social welfare enrolment, which contributed to higher overall weighted scores compared to their counterparts in Vizianagaram. This may reflect differences in the reach of government programs and digital infrastructure between the districts.

Gender and Social Capital

Female respondents, particularly those active in SHG/ Society/ FPOs, tended to have higher character and capacity scores. SHG/ Society/ FPO membership was strongly correlated with better repayment histories and access to social welfare schemes. This finding underscores the role of social capital and collective action in enhancing creditworthiness among marginalized groups.

Digital Inclusion

A clear positive association was observed between digital engagement (years of mobile phone use, payment app installation, social media activity) and overall credit scores. Farmers with higher digital literacy not only scored better in character but also benefitted from improved access to information, markets, and financial services.

Social Welfare Scheme Participation:

Enrolment in government welfare schemes was a significant driver of higher capacity and conditions scores. These schemes provided income stability, risk mitigation, and improved access to formal credit channels.

Correlation and Predictive Analysis

Correlation analysis revealed that character and capacity scores were most strongly associated with overall weighted credit scores ($r = 0.62$ and $r = 0.59$, respectively). Collateral and conditions also showed moderate positive associations, while capital was somewhat less predictive, likely due to

the relatively uniform asset base among respondents. Regression models confirmed the significance of digital inclusion, SHG/ Society/ FPO membership, and social welfare enrolment as predictors of credit approval.

Summary

The alternative credit scoring model, grounded in the 5C's framework and enriched with alternative data, provided a nuanced and inclusive assessment of smallholder creditworthiness. The results highlight both the progress and persistent gaps in rural financial inclusion. While digital and social innovations have improved credit access for many, structural barriers remain for the most vulnerable. The findings underscore the value of integrating alternative data into credit appraisal and the need for targeted policy interventions to support conditionally approved and declined farmers.

Discussion

Methodological Insights

The operationalization of the 5C's using both traditional and alternative data offers a robust framework for rural credit appraisal. Notably, Character (including digital and social indicators) and Capacity (income, cropping, social welfare) emerged as the most predictive of creditworthiness. This aligns with recent literature emphasizing the value of behavioural and social data in financial services (22). Despite being an important component in the traditional risk assessment system, the capital's contribution to credit risk assessment is lower as compared to other Cs in the current paper. The observation may be a result of homogenous landholdings, fragmented land parcels, and improper or incomplete land documents of the respondents that may jeopardise their access to institutional finance. Availability of various subsidy schemes may further reduce the farmers' reliance on capital thus making it an insignificant pre-emptor of credit risk.

There was a study on fair-algorithmic models built specifically for risk assessment of microfinance profiles who are creditworthy but are subjected to financial exclusion. They opined that efficient credit scoring models focus on both fairness metrics and predictive performance. The study emphasized real-time trade-offs between fairness constraints and utility of the model while being focused on monitoring across borrower

subgroups. The research affirmed that inclusive rural credit models should incorporate fairness checks, not just alternative data enrichment. The research affirmed that credit risk assessment systems must blend fairness metrics with alternative data enrichment to serve rural customers in an inclusive manner (23).

Digital and Social Inclusion

The strong predictive power of digital inclusion variables (years since using mobile phone, payment app usage, social media) reflects the growing importance of digital footprints in rural India. SHG/Society/FPO membership and social welfare scheme participation further enhance the reliability of borrowers, supporting the expansion of group-based lending and social collateral models.

Past study recommended a "Humble AI" approach for high-stakes decisions, highlighting the fact that model outputs should be considered as error-prone and accompanied by clear unreliability, monitoring, and inflation/human-override mechanisms when confidence is low. Such framing is beneficial for alternative-data-based credit risk assessment as it builds trust, documentation, and accountability apart from just predictive accuracy (24).

Earlier research recognized interpretability as an integral part of trustworthy algorithmic frameworks, more so in scenarios where decisions impact the availability of essential services. They deliberated upon the role of explanations in enabling contestability, governance, and user acceptance that are key requisites of regulated financial systems. The paper differentiated technical interpretability from stakeholder-side explanations, thus enabling the alignment with decision accountability. In alternative data-enabled credit assessment, interpretability assists credit providers in justifying approvals/declines and ensuring fair decisions for borrowers (25).

Policy and Practice Implications

For lenders, integrating alternative data into credit scoring can significantly expand the pool of eligible borrowers and reduce default risk (26).

For policymakers, promoting digital literacy, SHG formation, and social welfare enrolment can have multiplier effects on financial inclusion (27).

For researchers, the 5C's mapping provides a replicable model for other regions and contexts.

Previous research integrated ethics-based AI auditing and emphasised value-based needs, stressing upon the value-based needs such as bias controls, and accountability. The research suggested building a transparent, traceable, and user-focused explanation-based Decision Support System (DSS) pipeline instead of considering ethics as a mere audit parameter. The system facilitated governance practices such as regular bias audit, documentation, and escalation pathways for disputed transactions which is critical to implement alternative credit scoring as an ethical DSS for financial institutions lending credit invisibles in the rural territories (28).

Conclusion

This methodological paper demonstrates that an alternative, weighted credit scoring model mapping both traditional and alternative data to the 5C's can enhance the prediction and inclusion of smallholder farmers in formal credit systems. The approach identifies most farmers as "conditionally approved," highlighting the need for risk mitigation tools such as guarantees or insurance. Policymakers and financial institutions should mainstream alternative data in rural credit appraisal and invest in digital and social infrastructure to bridge the rural credit gap.

Limitations

The sample is limited to two districts and may not capture wider heterogeneity, some variables are self-reported and may be subject to recall bias, and the cross-sectional design limits causal inference.

Future Research

Longitudinal studies to assess the impact of digital adoption on credit outcomes, and experimental validation of the alternative credit scoring model in partnership with lenders.

Abbreviations

FPO: Farmer Producer Organization, PMJDY: Pradhan Mantri Jan Dhan Yojana, r: Correlation Coefficient, SD: Standard Deviation, SHG: Self Help Group.

Acknowledgement

The authors gratefully acknowledge the support and assistance received from the M.S. Swaminathan School of Agriculture, Centurion University of Technology and Management, Odisha, in facilitating data collection for this study.

We declare no conflicts of interest related to this research.

Author Contributions

Anil Kumar Jonnalagadda: performed the experiments, analysed the data, wrote the initial draft of the manuscript, Ramesh Babu S: designed the study, supervised the project. All authors reviewed and approved the final version.

Conflicts of Interest

The authors of the current research affirm that there are no conflicts of interest, whatsoever, with this publication.

Data Availability

The datasets generated and analysed during the present study are available from the corresponding author on reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

The authors affirm that artificial intelligence (AI) assistance (ChatGPT, OpenAI) was deployed purely for editing and improving the interpretability of the manuscript. All scientific data was collected and interpreted by the authors.

Ethics Approval

The present research obtained joint ethical approval from the Institutional Review Boards and Research Ethics Boards of KL Education Foundation, Guntur, Andhra Pradesh, India and Centurion University of Technology and Management, Guntur, Andhra Pradesh, before collection of the data. All processes that involved human respondents were carried out as per the guidelines of institutional ethical committee and principles of World Medical Association Declaration of Helsinki (2013). All the participants joined the survey voluntarily and provided a prior written consent. The respondents understood the objectives of the survey, anonymized use of data for academic purposes, and about the option of withdrawing at any point in time. To ensure utmost confidentiality, personal identifiers were hidden and responses were encoded. Secure storage of data and aggregate reporting ensured the privacy and anonymity of the participants.

Funding

The authors have not received any kind of grant from public, private, or nonprofit organizations for undertaking present study.

References

- Banerjee AV, Duflo E. Do firms want to borrow more? Testing credit constraints using a directed lending program. *Review of Economic Studies*. 2014 Apr 1; 81(2):572-607. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=316587
- Binswanger HP, Khandker SR. The impact of formal finance on the rural economy of India. *The Journal of Development Studies*. 1995 Dec 1; 32 (2):234-62. <https://doi.org/10.1080/00220389508422413>
- Burgess R, Pande R. Do rural banks matter? Evidence from the Indian social banking experiment. *American economic review*. 2005 Jun 1;95(3):780-95. <https://doi.org/10.1257/0002828054201242>
- Chakrabarty KC. Financial inclusion: A road India needs to travel. *RBI Bulletin*, November. 2011 Oct: 1851-56. https://www.rbi.org.in/scripts/BS_ViewBulletin.aspx?Id=12680
- RBI. Report of the Internal Working Group to Review Agricultural Credit. *Indian Journal of Agricultural Economics*. 2020 Apr; 75 (2): 233-240. <https://isaeindia.org/wp-content/uploads/2020/11/05-Review-Article-1-by-Vijaya-Venkatesh.pdf>
- Stiglitz JE, Weiss A. Credit rationing in markets with imperfect information. *American Economic Review*. 1981;71(3):393-410. <https://www.jstor.org/stable/1802787>
- Berger AN, Udell GF. A more complete conceptual framework for financing of small and medium enterprises. *World Bank Publications*. 2005. Working Paper No. 3795: 1-31. <https://ssrn.com/abstract=874825>
- Fatoki O, Asah F. The impact of firm and entrepreneurial characteristics on access to debt finance by SMEs in King Williams' town, South Africa. *International Journal of Business and management*. 2011 Aug 1; 6 (8): 170. <https://doi.org/10.5539/ijbm.v6n8p170>
- Demirgüç-Kunt A, Klapper L, Singer D, Ansar S, Hess J. *The Global Findex Database 2017: Measuring financial inclusion and opportunities to expand access to and use of financial services*. *The World Bank Economic Review*. 2020 Feb 1; 34 (Supplement_1):S2-8. <https://doi.org/10.1093/wber/lhz013>
- Frost J, Gambacorta L, Huang Y, Shin HS, Zbinden P. BigTech and the changing structure of financial intermediation. *Economic policy*. 2019 Oct 1; 34 (100): 761-99. <https://ssrn.com/abstract=3369011>
- Jagtiani J, Lemieux C. The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. *Financial Management*. 2019 Dec; 48 (4): 1009-29. <http://dx.doi.org/10.21799/frbp.wp.2018.15>

12. Agarwal S, Alok S, Ghosh P, Gupta S. Financial inclusion and alternate credit scoring: Role of big data and machine learning in fintech. *Indian School of Business*. 2019 Dec 21. <https://doi.org/10.2139/ssrn.3507827>
13. Duvendack M, Sonne L, Garikipati S. Gender inclusivity of India's digital financial revolution for attainment of SDGs: Macro achievements and the micro experiences of targeted initiatives. *The European Journal of Development Research*. 2023;35(6):1369–1391. <https://doi.org/10.1057/s41287-023-00585-x>
14. Reddy AA, Bantilan M. Regional disparities in Andhra Pradesh, India. *Local Economy: The Journal of the Local Economy Policy Unit*. 2012 Nov 13;28(1):123–35. <https://doi.org/10.1177/0269094212463791>
15. Kumar A, Das R, K S A, Bathla S, Jha GK. Examining institutional credit access among agricultural households in eastern India: Trends, patterns and determinants. *Agricultural Finance Review*. 2020 Oct 3;81(2):250–64. <https://doi.org/10.1108/afr-04-2020-0054>
16. Giné X, Klöpper S. Credit constraints as a barrier to technology adoption by the poor. *UNU World Institute for Development Economics Research (UNU-WIDER) Research Paper*. 2006 Sep (2006/104): 35. <http://documents1.worldbank.org/curated/en/142521468258303137/pdf/wps3665.pdf>
17. Karlan D, Ratan AL, Zinman J. Savings by and for the Poor: A Research Review and Agenda. *Review of Income and Wealth*. 2014 Mar; 60 (1): 36-78. <https://doi.org/10.1111/roiw.12101>
18. Björkegren D, Grissen D. Behavior revealed in mobile phone usage predicts credit repayment. *The World Bank Economic Review*. 2020 Oct; 34 (3) :618-34. <https://doi.org/10.1093/wber/lhz006>
19. Triki T, Faye I. Financial inclusion in Africa. *Tunis: African Development Bank*; 2013 Apr. Report No.: 556. https://www.rfilc.org/wp-content/uploads/2020/08/Financial_Inclusion_in_Africa.pdf
20. Shinde R, Kulkarni S. Credit scoring using smallholder agricultural data. *Comput Electron Agric*. 2020; 173:105410. <https://doi.org/10.1002/ijfe.3010>
21. Óskarsdóttir M, Bravo C, Sarraute C, Vanthienen J, Baesens B. The value of big data for credit scoring: Enhancing financial inclusion using mobile phone data and social network analytics. *Appl Soft Comput*. 2019; 74: 26-39. <https://doi.org/10.1016/j.asoc.2018.10.004>
22. Rodriguez C, Conrad J, Davico G, Lonie S, Denyes L. A New Banking Model for Africa: Lessons on digitization from four years of operations. 2019 Apr. 2-45. https://digilabfinance.org/sites/default/files/case-studies/2019-11/longitudinalstudy_newbankingmodelforafrica_final.pdf
23. Kozodoi N, Jacob J, Lessmann S. Fairness in credit scoring: Assessment, implementation and profit implications. *Eur J Oper Res*. 2022;297(3):1083–1094. <https://doi.org/10.1016/j.ejor.2021.06.023>
24. Knowles B, D'Cruz J, Richards JT, Varshney KR, Humble AI. *Commun ACM*. 2023;66(9):73–79. <https://doi.org/10.1145/3587035>
25. Yao C, Dastin J, Varshney KR. Trustworthiness and interpretability in algorithmic systems. *AI Ethics*. 2022; 2(3):387–405. 5. <https://doi.org/10.1007/s43681-022-00200-5>
26. Laine J, Minkkinen M, Mäntymäki M. Ethics-based AI auditing: A systematic literature review on conceptualizations of ethical principles and knowledge contributions to stakeholders. *Inf Manag*. 2024;61(5):103969. <https://doi.org/10.1016/j.im.2024.103969>
27. Kumar A, Sharma S, Mahdavi M. Machine Learning (ML) Technologies for Digital Credit Scoring in Rural Finance: A Literature Review. *Risks*. 2021;9(11):192. <https://doi.org/10.3390/risks9110192>
28. Berg T, Burg V, Gombović A, Puri M. On the Rise of FinTechs: Credit Scoring Using Digital Footprints. *Rev Financ Stud*. 2020; 33(7): 2845-2897. <https://dx.doi.org/10.2139/ssrn.3163781>

How to Cite: Jonnalagadda AK, Babu SR. Drivers of Credit Uptake by Smallholder Farmers: Empirical Evidence from India's Agricultural Sector. *Int Res J Multidiscip Scope*. 2026; 7(2): 110-119. DOI: 10.47857/irjms.2026.v07i02.08617