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Enhancing Credit Risk Management and Organizational Adaptation in Thai Agricultural Cooperatives

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ABSTRACT

Agricultural cooperatives in Thailand play a crucial role in providing deposit and credit services. Credit management faces challenges due to inadequate risk analysis, which can lead to non-performing loans (NPLs). This study develops a credit risk prediction model utilizing quantitative data, Machine Learning (ML), and Explainable AI (XAI) to improve organizational adaptation. Data from 300 cooperative members, supplemented by records from the National Statistical Office, were analyzed using the 5Cs framework (Character, Capacity, Capital, Collateral, Condition) to create profiles and predictive models employing decision trees, logistic regression, and artificial neural networks integrated with XAI. The findings indicate that Character and Collateral are most effectively modeled with decision trees, capacity with logistic regression, and Capital and Condition with neural networks combined with XAI. Accumulated local effects (ALE) highlighted key risk factors, including income, debt, default history, savings, and external variables. The integration of the 5Cs framework with ML and XAI enhances predictive accuracy, transparency, and data-driven decision-making. Change management strategies, such as personnel training, stakeholder engagement, and the promotion of technological understanding, are essential for sustainable adoption and utilization.

Keywords: Credit risk, Machine learning, Agricultural cooperatives, Explainable AI, Change management.

Introduction

Agricultural cooperatives in Thailand play a crucial role in deposit and loan systems by providing low-interest loans to members, supporting agricultural investments, and acting as financial intermediaries that promote economic opportunities (Agriinfo, 2023). Such access helps reduce economic inequality and stabilize community incomes. However, cooperatives face challenges in loan management, chiefly due to ineffective credit analysis, which may lead to the approval of loans that exceed members' repayment capacity, thereby elevating non-performing loans (NPLs) and affecting financial stability (Nor *et al*., 2021; Phan *et al*., 2023).

In the year 2023, Thailand was home to 3,193 agricultural cooperatives (Agriinfo, 2023). Conversely, non-agricultural cooperatives accounted for 91.67% of total credit, with savings cooperatives accounting for 89.20%, thereby accentuating the growing concern over non-performing loans (NPLs) and the imperative for more accurate credit evaluation. Decisions made by loan applicants are influenced by their financial condition, managerial attitude, and social capital (Phan *et al*., 2023), underscoring the significance of comprehensive risk assessment and data-driven insights. Credit officers play a crucial role in document verification, risk assessment, debt monitoring, and management of overdue accounts. The application of analytical insights such as repayment capacity, debt tracking, and NPL trend analysis can improve operational efficiency, reduce bad debts, and strengthen financial stability.

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The integration of Machine Learning (ML) and advanced data analytics has garnered significant attention, enabling the rapid processing of complex datasets to support enhanced credit decision-making. Nonetheless, technological adoption alone remains insufficient. The successful deployment of digital credit systems requires systematic Change Management, which encompasses modifications in organizational culture, the promotion of learning and innovation, fostering understanding of technological benefits, and strengthening leadership to guide change (Kotter, 1996; Cameron & Green, 2020; Prosci, 2022). From an organizational behavior perspective, effective change management involves considering personnel readiness, self-efficacy, and perceived managerial support (Lestari *et al*., 2022; Zulkarnain *et al*., 2024; Shanti *et al*., 2025). Engaging staff in the design and enhancement of processes reduces resistance and promotes sustainable technology adoption (Awad & Martín-Rojas, 2024; Michelotto & Joia, 2024). Such initiatives not only improve credit assessment efficiency and reduce non-performing loans (NPLs) but also encourage staff adaptation, develop data-driven decision-making skills, enhance team collaboration, and contribute to long-term financial stability for members (Shanti *et al*., 2025). Furthermore, systematic change management enables cooperative organizations to respond effectively to market complexities and community needs (Shanti *et al*., 2025; Awad & Martín-Rojas, 2024).

This study seeks to develop and evaluate a data-driven credit risk prediction model for agricultural cooperatives, whilst concurrently fostering organizational adaptation and change management strategies. The integration of data-driven methodologies with change management enhances the precision of risk assessments, reduces bad debts, and supports continuous operational improvements, ultimately providing a practical framework for sustainable and efficient cooperative management.

Literature Review

Credit Analysis

The analysis of credit constitutes a fundamental element of risk management within financial institutions. It aids lenders in assessing the likelihood of default and in determining appropriate measures (Noriega *et al*., 2023). Contemporary research further underscores that effective credit assessment enhances portfolio stability and diminishes institutional vulnerability to economic shocks. From a qualitative perspective, the esteemed framework is the 5Cs of credit, comprising Character, Capacity, Capital, Collateral, and Conditions. This framework enables banks to evaluate both the borrower's attributes and external factors (Jakubik & Teleu, 2025) while also promoting a more transparent and explainable decision-making process aligned with emerging standards in risk analytics (Nallakaruppan *et al*., 2024).

The term 'Character' pertains to the credibility and financial discipline of the borrower, assessed based on the history of debt repayment and prior credit utilization (Al-Slehat *et al*., 2024). 'Capacity' concerns the borrower's ability to settle debt, measured by current income, debt burden, and credit usage patterns (Jakubik & Teleu, 2025). 'Capital' refers to the reserve funds or assets held by the borrower; although it is not directly the principal amount, it functions to mitigate risk (Nallakaruppan *et al*., 2024). 'Collateral' signifies the security or guarantor that provides assurance to the financial institution in the event of borrower default (Al-Slehat *et al*., 2024). Finally, 'Conditions' encompass external factors such as economic circumstances, financial uncertainties, or geopolitical influences that impact the borrower's repayment capacity (Jakubik & Teleu, 2025). Recently, the integration of Machine Learning (ML) and Explainable AI (XAI) within the 5Cs framework has been undertaken to enhance accuracy and transparency in risk assessment. For example, Nallakaruppan *et al*. (2024) employ XAI to assist banks in understanding model decisions, while Noriega *et al.* (2023) discovered that ensemble algorithms such as XGBoost yield superior results compared to traditional models. Furthermore, research published in the Journal of Organizational Behavior Research underscores the impact of macroeconomic and institutional factors on credit risk. Huyen *et al.* (2023) find that public debt influences economic growth in Asia in a non-linear manner, potentially affecting debtors' repayment capacity. Viet *et al*. (2023) show that the non-performing loan (NPL) ratio of commercial banks in Vietnam depends on their financial characteristics. Furthermore, Linh *et al*. (2024) propose that the green credit program significantly affects sustainable economic development, demonstrating the impact of lending policies on social and environmental risks.

In conclusion, the 5Cs framework continues to play a significant role in qualitative analysis. However, it should be combined with quantitative techniques and modern technologies to improve accuracy, flexibility, and transparency in credit risk assessment today.

Application of Machine Learning in Credit Analysis

In recent years, Machine Learning (ML) has assumed a significant role in the assessment of credit risk. This prominence is attributable to its capacity to efficiently analyze extensive and complex datasets (Noriega *et al*., 2023; Samaranayake *et al*., 2024). Various Machine Learning techniques, including Decision Tree, Random Forest, Gradient Boosting, and Logistic Regression, have gained prominence for their effectiveness in accurately classifying borrowers by risk level and managing data imbalance (Selby Nkambule *et al*., 2024; Bhandary & Ghosh, 2025). Furthermore, Explainable AI (XAI) has been integrated with machine learning (ML) to enhance transparency in decision-making processes. This integration enables financial institutions to verify the rationale underpinning borrower classification and to establish greater trust in risk assessment procedures (Nallakaruppan *et al*., 2024). Numerous studies have demonstrated that ensemble algorithms such as XGBoost and Random Forest produce more precise results than traditional linear models, particularly when handling borrower data with overlapping characteristics (Noriega *et al*., 2023; Pisano *et al*., 2023; Liu & Tham, 2024).

Furthermore, recent research has demonstrated that Machine Learning (ML) can be integrated with macroeconomic and economic data, such as the Non-Performing Loan (NPL) index, economic growth metrics, or green credit initiatives, to enhance the effectiveness of risk assessment and assist in policymaking (Huyen *et al*., 2023; Viet *et al*., 2023; Linh *et al*., 2024). While the use of Machine Learning (ML) and Explainable Artificial Intelligence (XAI) within the 5Cs framework has been extensively evaluated in commercial banks, there remain limitations to implementing these technologies in agricultural cooperatives. The assessment of member risk in cooperatives predominantly depends on qualitative analyses and historical data. Conducting experiments to apply ML/XAI to member data—such as income, debt burdens, savings, and repayment behaviors—has the potential to improve both accuracy and transparency in credit risk assessment. Moreover, this approach could aid policy decision-making within cooperatives and promote more efficient loan allocation in the context of agricultural cooperatives.

Management of Change in the Application of Machine Learning / Explainable Artificial Intelligence (XAI) for Agricultural Cooperatives

The integration of Machine Learning (ML) and Explainable AI (XAI) into the credit analysis procedures of agricultural cooperatives exemplifies the potential to improve precision and transparency. Nonetheless, the effective implementation of these systems continues to depend on proficient change management within the organization (Kotter, 1996; Cameron & Green, 2020; Prosci, 2022). Change Management constitutes a systematic process designed to modify organizational culture, employee behaviors, and workflows to enhance readiness for the acceptance and effective utilization of emerging technologies (Prosci, 2022). Within the realm of agricultural cooperatives, change management is of considerable importance, as loan officers often adhere to traditional practices and may resist data-driven credit analysis systems. Establishing a shared understanding of the advantages of ML/XAI, enhancing self-efficacy, and obtaining executive management support are critical mechanisms that can mitigate resistance and foster the sustainability of technological implementation (Kotter, 1996; Cameron & Green, 2020; Prosci, 2022).

Research indicates that systematic change management should encompass personnel participation in the design and enhancement of workflows, training and skill development in the use of technology, and the establishment of technical and administrative support structures (Prosci, 2022). Such measures not only enable personnel to effectively utilize ML/XAI for risk assessment of cooperative members but also foster behavioral and organizational outcomes, including staff adaptability, the development of data-driven decision-making skills, strengthened inter-team collaboration, and the sustainable enhancement of cooperative members' financial security. Therefore, the integration of Machine Learning (ML) and Explainable Artificial Intelligence (XAI) with change management strategies provides an appropriate conceptual framework for agricultural cooperatives seeking to improve loan procedures, mitigate risks associated with non-performing loans (NPLs), and establish sustainable financial stability within the community (Kotter, 1996; Cameron & Green, 2020; Prosci, 2022).

Materials and Methods

The data utilized in this research are categorized into two components. First, the survey questionnaire administered to loan applicants in collaboration with the cooperative employs stratified random sampling based on regional distribution across Thailand, comprising 300 sets. The instrument seeks to gather data on demographics, household income and expenses, household debt, savings behavior, borrowing history from the cooperative, assets and collateral, attitudes towards credit access, financial behavior, external factors influencing debt repayment capacity, access to alternative funding sources outside the cooperative, and opinions on credit accessibility. These data are collected using a five-point rating scale. The validity of this instrument has been confirmed through a content validity assessment. This research project has obtained approval from the Human Research Ethics Committee of Mahasarakham University (Approval Number 524-501/2568) prior to data collection. Participants were informed of their rights, data confidentiality, and provided voluntary informed consent. The collected data are stored in an anonymized manner to protect participant anonymity. The secondary data consist of datasets obtained from the National Statistical Office, including income, liabilities, expenses, and assets of agricultural households. These data are employed to present an overview of the agricultural sector and to support detailed analysis based on primary data.

Descriptive Profiles of the 5C Dimensions

To gain an intuitive understanding of borrowers' strengths and weaknesses within the traditional 5C credit framework, we initially developed composite profiles for each dimension: Character, Capacity, Capital, Collateral, and Condition. For each dimension, the underlying Likert-scale indicators (ranging from 1 to 5 or 6) were averaged both within each region and across the entire sample. The resulting mean scores were illustrated using radar charts, where each spoke signifies an individual indicator, the radius denotes the average score, and overlaid polygons facilitate comparison between regional profiles and the overall mean. This descriptive procedure summarizes the joint distribution of the questionnaire indicators and provides a substantive context for subsequent predictive modeling.

Predictive Model for Default Risk

In the subsequent phase, we developed a non-parametric classification model to forecast binary default outcomes based on the 5C indicators. The analytical dataset comprised all respondents with complete data on the selected survey items and the observed loan performance indicator (default versus non-default). All predictors were categorized as either ordinal or discrete numerical variables. The data were randomly partitioned into a training set (80%) and a hold-out test set (20%), stratified by the default label. Considering the potential nonlinearity and interaction effects among the 5C dimensions, a Random Forest classifier was selected as the primary predictive model. This forest consisted of 500 trees employing bootstrap sampling and random feature selection at each split; the maximum depth of the trees was left unrestricted. The performance of the model on the test set was evaluated using the area under the receiver operating characteristic curve (ROC-AUC), which offers a threshold-independent measure of discriminative ability between defaulting and non-defaulting borrowers.

Model-Level Interpretability Using ALE Plots

To translate the black-box predictions into communication-relevant insights, we employed one-dimensional Accumulated Local Effects (ALE) plots on the fitted Random Forest model. ALE plots measure the average marginal effect of a predictor on the predicted probability of default, while considering dependencies among predictors. Unlike partial dependence plots, ALE avoids extrapolation into regions of the feature space with sparse data, thus rendering it more appropriate for correlated socio-economic indicators. Our focus was directed towards six substantively significant indicators: income, household debt, default history, regular saving, and two metrics capturing exposure to external shocks. For each indicator, a discrete ALE profile was computed across its observed response categories, utilizing the Random Forest's predicted default probabilities as the response surface. The ALE values were normalized to have a mean of zero, with positive values indicating an increase, and negative values indicating a decrease, in the predicted default risk relative to the sample mean.

Results and Discussion

The analysis results of the 5Cs credit assessment indicate that Character and Collateral are suitable for the Decision Tree approach. This is because they enable the creation of interpretable rules and facilitate clear risk group classification. Specifically, the Decision Tree for Character achieves an accuracy of approximately 0.967and an F 1 score of about .0.929Meanwhile, the Collateral classification is perfect, with an accuracy and F 1score of .%100For Capacity, Logistic Regression yields high precision with an accuracy around 0.878and an F 1score of approximately 0.874, and it can be interpreted economically to determine the Debt-to-Income ratio and debt ceiling. Capital and condition are best suited for Artificial Neural Networks (ANN) combined with Explainable AI (XAI) due to their ability to accurately capture non-linear relationships and interactions among financial status and contextual factors, with both models achieving an accuracy and F 1score close to 1.00for capital, and approximately 0.956for condition. In both cases, it is recommended to utilize cross-validation and XAI to ensure transparency and prevent overfitting. Overall, the Moderate risk group poses a challenge for several models. To enhance stability, approaches such as ensemble methods, calibration, or ordinal modeling should be employed. Practical policies derived from these results include monitoring high-risk borrowers, setting debt or collateral limits, supporting savings and supplemental income, and implementing measures to mitigate risks from crises or external factors.

This table offers a comprehensive summary of the predictive models employed for each of the 5C dimensions: Character, Capacity, Capital, Collateral, and Condition. It encompasses their respective performance metrics, namely, Accuracy, Balanced Accuracy, F1 Score, and ROC-AUC, as well as essential analytical insights and associated policy recommendations for cooperative management. All references to tables and figures are duly noted within the text. **(Table 1)**

Table 1. Predictive Models, Performance Metrics, Key Insights, and Policy Recommendations for 5Cs Credit Assessment in Thai Agricultural Cooperatives**.**

	Predictive Model & Metrics	**Key Insights**
Character	Decision Tree: - Accuracy ≈ 0.967 - Balanced Acc ≈ 0.933 - F1 ≈ 0.929 - ROC-AUC ≈ 0.940 - The tree constructs interpretable rules for behavioral or categorical analysis.	Clear decision rules; effective classification of high-risk borrowers
Capacity	Logistic Regression: - Accuracy ≈ 0.878 - Balanced Acc ≈ 0.874 - F1 ≈ 0.874 - ROC-AUC ≈ 0.935 Decision Tree: - Accuracy ≈ 0.833 - Balanced Acc ≈ 0.833 - F1 ≈ 0.835	Captures repayment capacity; supports Debt-to-Income (DTI) and credit limit assessment
Capital	ANN (MLP) + XAI: - Accuracy/Balanced/F1/ROC-AUC ≈ 1.00 - Effectively capturing non-linear patterns and high interactions	Captures non-linear interactions in financial data; high prediction accuracy
Collateral	Decision Tree: - Accuracy/Balanced/F1 = 100% - Logistic Regression: - Accuracy ≈ 0.889 - Balanced Acc ≈ 0.667 - F1 ≈ 0.838 - ROC-AUC = 1.00	Enables precise identification of collateral thresholds; interpretable decision rules

Condition	ANN + XAI: - Accuracy ≈ 0.956 - Balanced Acc ≈ 0.954 - F1 ≈ 0.956 - ROC-AUC ≈ 0.982 Decision Tree: - Accuracy ≈ 0.667 - Balanced Acc ≈ 0.669 - F1 ≈ 0.671	Captures complex, multidimensional contextual factors

Machine Learning has the potential to be developed into an effective tool for predicting the risk of loan approval for agricultural cooperatives in Thailand. The suitability of the model is contingent upon the data characteristics of each of the 5Cs components, as outlined below:

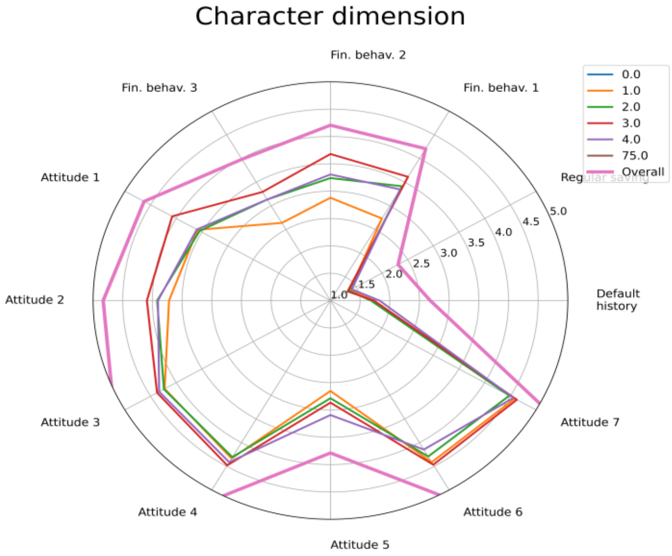
1. The data type information indicating categorical and behavioral data demonstrates that the Decision Tree model is highly effective, producing clear, easily interpretable decision rules that facilitate precise screening of high-risk borrowers.
2. Capacity: Economic and financial data; suitable models are Logistic Regression and Decision Tree for assessing repayment potential, determining the Debt-to-Income Ratio, and setting credit limit thresholds.
3. Capital comprises data with intricate relationships, characterized by non-linear interactions. The Artificial Neural Network (ANN) model, when integrated with Explainable AI (XAI) techniques, is well-suited for analyzing complex patterns in financial data and further enhances transparency in decision-making processes.
4. An assessment of collateral valuation revealed that the Decision Tree model can effectively identify the optimal cut-point and threshold for the loan amount.
5. The condition involves multidimensional and highly overlapping contextual factors. The ANN + XAI model is appropriate because it can effectively learn non-linear relationships and interactions among variables.

As summarized in **Table 2**.

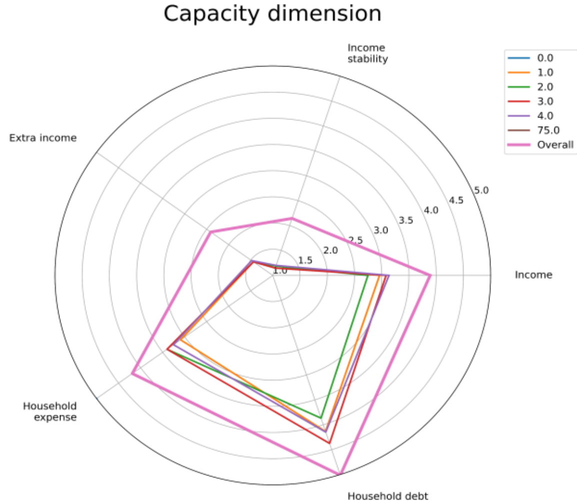
Table 2. Data Characteristics, Suitable Models, and Applications for 5Cs Credit Assessment

5Cs	Data Characteristics	Suitable Model	Rationale / Application
Character	Categorical / Behavioral Data	Decision Tree	Able to formulate precise and comprehensible decision rules suitable for identifying high-risk borrowers.
Capacity	Financial/Economic Data	Logistic Regression, Decision Tree	Assessing the ability to service debt, calculating the Debt-to-Income Ratio, and establishing the maximum credit limit.
Capital	Non-linear / Interactions	Artificial Neural Network (ANN) + Explainable AI (XAI)	Identify intricate financial patterns and facilitate transparency in decision-making.
Collateral	Collateral Valuation	Decision Tree	Establish the appropriate cut-point and threshold for the credit limit effectively.
Condition	Multidimensional Contextual Factors	ANN + XAI	Acquire knowledge regarding the nonlinearities and interactions of complex contextual variables.

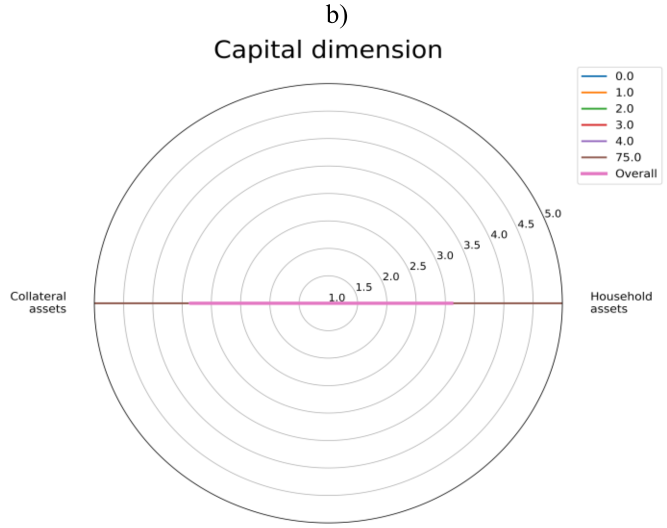
The radar profiles of the 5C dimensions are depicted in **Figure 1**, illustrating the five dimensions comprehensively. Panel (a) indicates that the Character dimension exhibits overall strength: consistent saving behavior, the three financial behavior items, and attitudes 3–7 all attain relatively high mean scores near the upper end of the scale. Conversely, the default-history item is positioned closer to the center of the radar, suggesting that historical repayment issues are more prevalent than other character-related deficiencies. The regional polygons largely coincide with the overall profile, suggesting that character traits are relatively consistent across regions **(Figure 1)**.


Character dimension
Fin. behav. 2
Fin. behav. 1
Fin. behav. 3
Regular saving
Attitude 1
Attitude 2
Default history
Attitude 3
Attitude 7
Attitude 4
Attitude 6
Attitude 5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
0.0
1.0
2.0
3.0
4.0
75.0
Overall

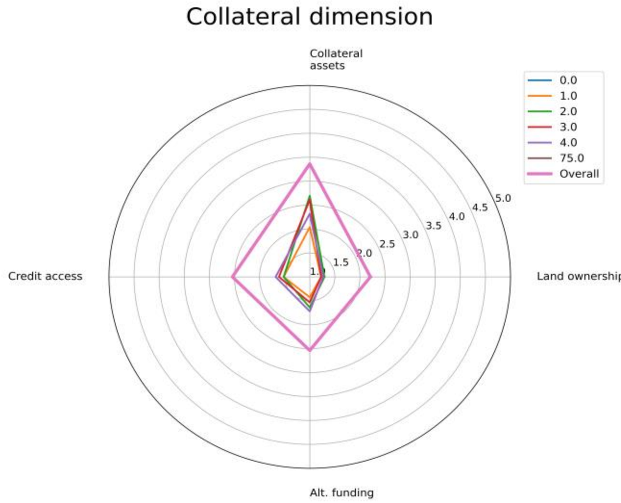
a)


Capacity dimension
Income stability
Extra income
Income
Household expense
Household debt
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
0.0
1.0
2.0
3.0
4.0
75.0
Overall

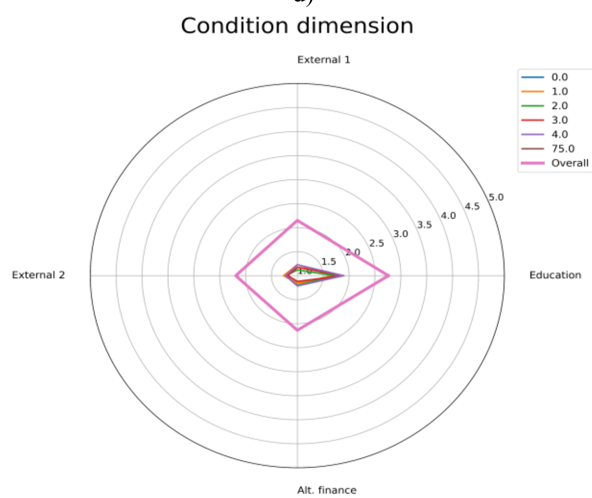
b)


Capital dimension
Collateral assets
Household assets
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
0.0
1.0
2.0
3.0
4.0
75.0
Overall

c)



d)



e)

Figure 1. Radar profiles of the five 5C credit dimensions.
1-Panel (a-Character), 2-Panel (b-Capacity), 3-Panel (c-Capital), 4-Panel (d-Collateral), and 5-Panel (e-Conditions).

Figure 1, Panel (b) underscores a more heterogeneous pattern regarding the Capacity dimension. Average income levels are moderate to high; however, income stability and additional income scores are significantly lower, indicating that many borrowers depend on unstable or undiversified income sources. Concurrently, household expenses, particularly household debt, occupy the outer spokes of the radar chart. This combination of moderate income, low stability, and high indebtedness suggests a potentially limited repayment capacity for a noteworthy subset of borrowers. Regional differences are observed but generally conform to the same overarching pattern as the overall profile.

Panels (c)–(e) summarize the dimensions of Capital, Collateral, and Condition. Capital, as measured by household and collateral assets, shows relatively similar, moderately high mean scores, with only limited regional variation. This indicates that asset holdings are predominantly an individual characteristic rather than a regional one. The Collateral dimension encompasses land ownership, collateral assets, access to credit, and alternative funding sources. Land ownership registers score relatively low; however, indicators related to collateral assets and credit access tend to be higher. This suggests that many borrowers are able to rely on collateral or credit channels even in the absence of land titles. Conversely, the Condition dimension exhibits the lowest overall levels among the five Cs. Education scores are moderate, whereas the external-condition items and alternative finance indicators display low averages. These findings imply widespread exposure to adverse external conditions and limited access to financial services that buffer. Collectively, the radar profiles indicate that the primary vulnerabilities are concentrated within the Capacity and Condition dimensions, while the Character, Capital, and Collateral dimensions appear comparatively more robust.

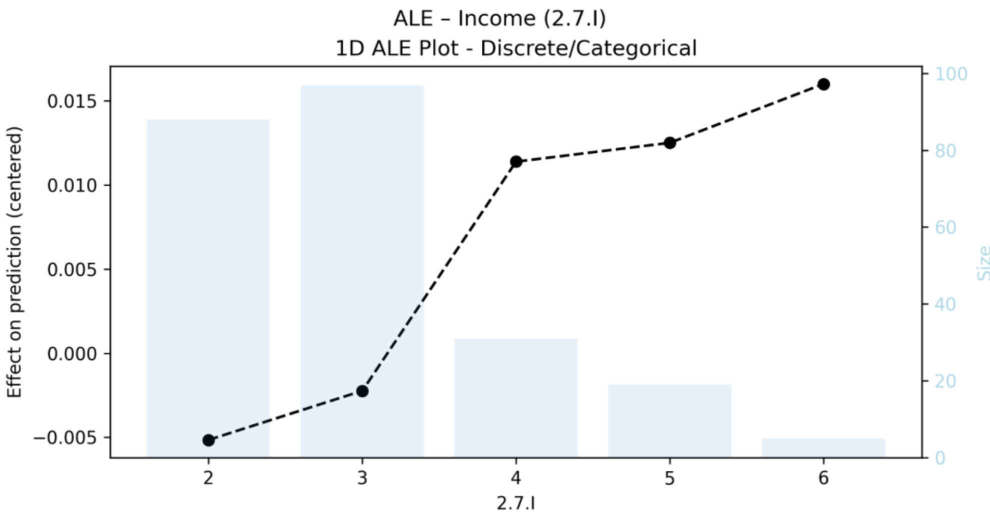
The ALE profiles for key predictors are presented in **Figure 2**, which illustrates the ALE profiles for the six primary predictors derived from the Random Forest model. Panel (a) shows that higher income brackets are associated with a slight reduction in centered ALE values at the lower end of the spectrum, with a progressive shift towards positive effects at higher income levels. This pattern indicates that, when other indicators are held constant, higher reported income generally correlates with lower predicted default risk, though the marginal impact diminishes as income moves into higher categories.

Panel (b) displays the ALE for household debt. At low to moderate debt levels, the centered effect is approximately zero or marginally negative; however, it becomes positive at the highest categories, indicating that only substantially elevated levels of household debt significantly augment the model-implied default probability. This threshold pattern aligns with the descriptive radar profile, where the outer spokes appear at elevated debt scores.

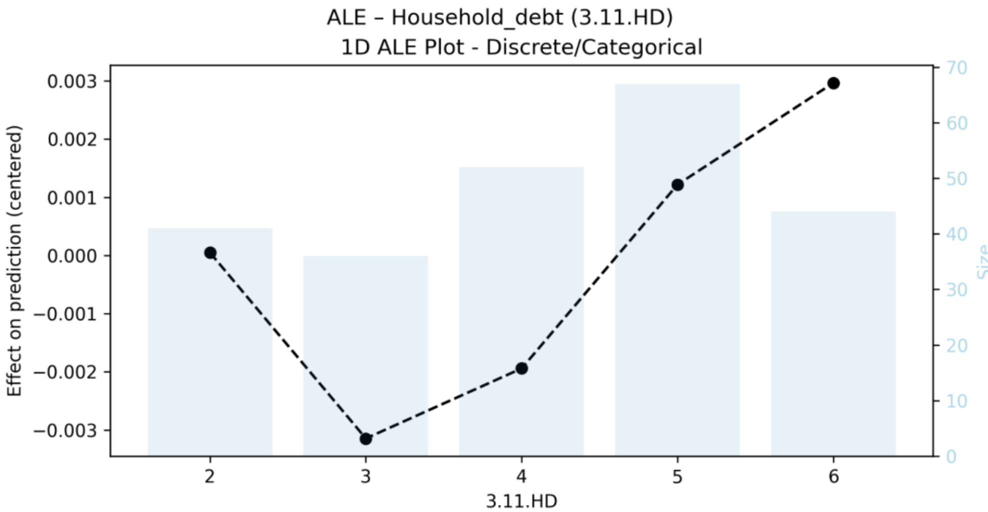
Panels (c) and (d) delineate the behavioral indicators. In the default historical data, transitioning from the low-risk to the higher-risk category results in a significant positive escalation in ALE, signifying a considerable increase in the predicted likelihood of default for borrowers exhibiting problematic repayment histories. Conversely, regular saving demonstrates an inverse relationship: elevated saving scores correlate with more negative ALE values, aligning with the interpretation that consistent, disciplined saving behaviors diminish default risk within the model.

Finally, panels (e) and (f) illustrate the impacts of the two external-shock indicators. In both instances, the ALE curves ascend from near zero to positive values as they correspond to higher shock categories, indicating that borrowers reporting greater exposure to adverse external conditions are associated with an increased predicted default risk, even when controlling for the other 5C indicators. The magnitude of these effects is less pronounced than that of default history but is comparable to the effects of income and household debt.

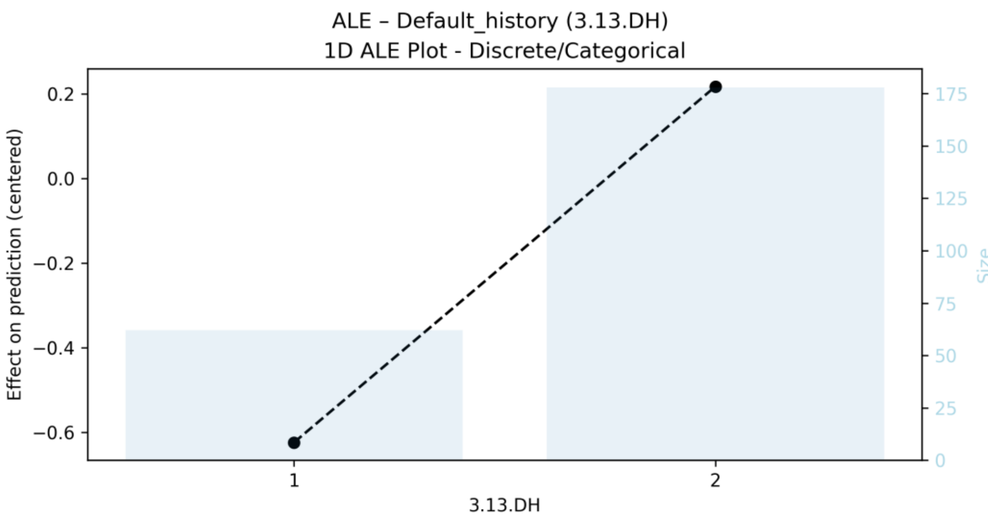
Overall, the ALE analysis confirms that the model's default predictions are influenced by a combination of structural factors (income and debt), behavioural characteristics (default history and saving behaviour), and contextual vulnerabilities (external shocks). These model-based profiles complement the descriptive radar charts and offer a more detailed understanding of how specific 5C indicators contribute to credit risk at the margin **(Figure 2).**



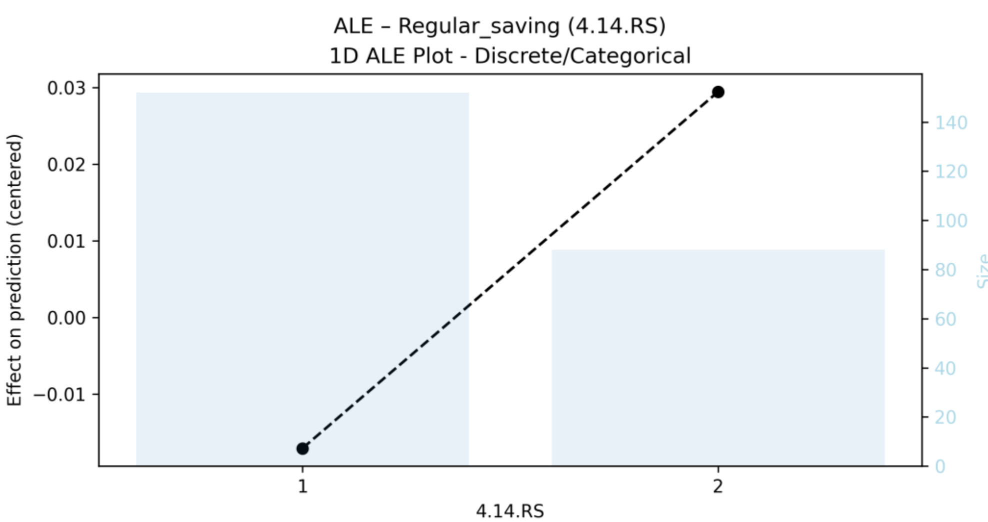
a)


ALE – Household_debt (3.11.HD)
1D ALE Plot - Discrete/Categorical
Effect on prediction (centered)
0.003
0.002
0.001
0.000
−0.001
−0.002
−0.003
Size
70
60
50
40
30
20
10
0
2
3
4
5
6
3.11.HD

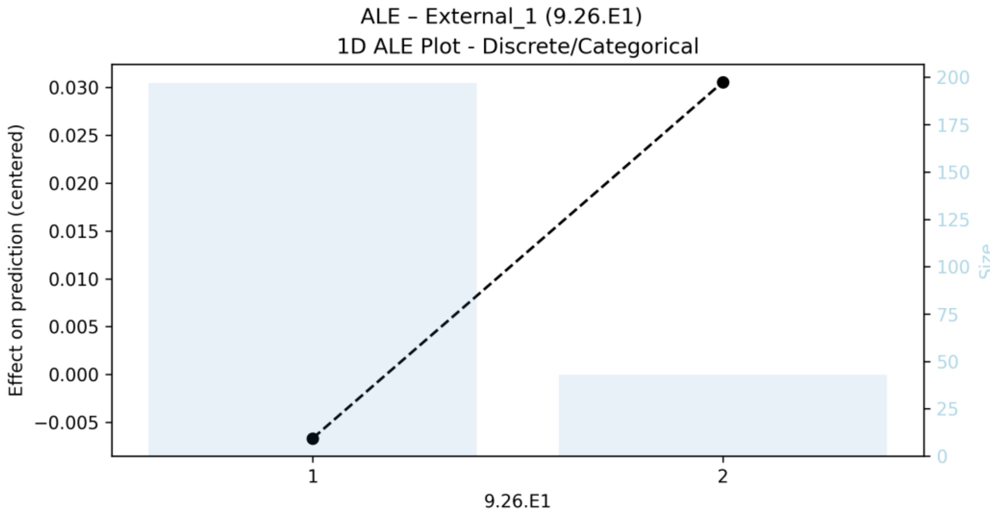
b)


ALE – Default_history (3.13.DH)
1D ALE Plot - Discrete/Categorical
Effect on prediction (centered)
0.2
0.0
−0.2
−0.4
−0.6
Size
175
150
125
100
75
50
25
0
1
2
3.13.DH

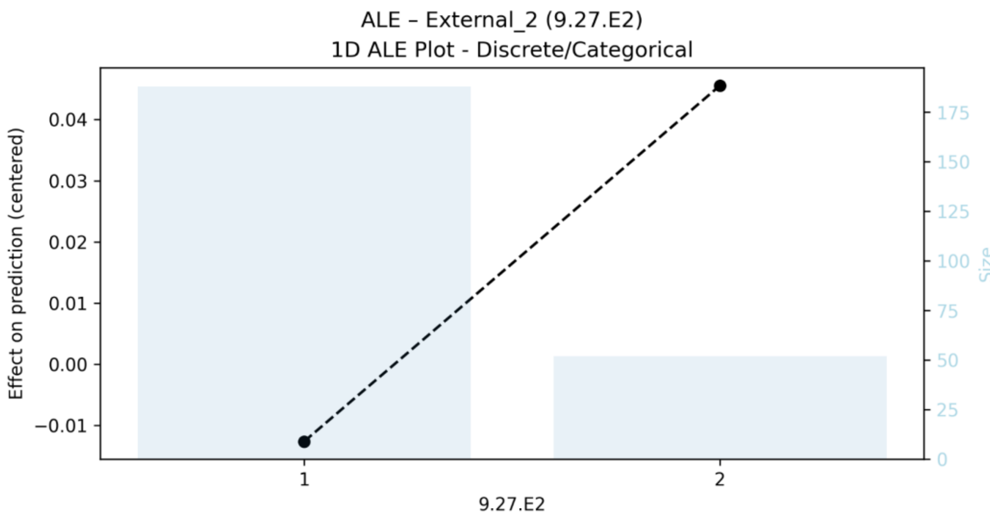
c)


ALE – Regular_saving (4.14.RS)
1D ALE Plot - Discrete/Categorical
Effect on prediction (centered)
0.03
0.02
0.01
0.00
−0.01
Size
140
120
100
80
60
40
20
0
1
2
4.14.RS

d)



e)



f)

Figure 2. Accumulated local effects (ALE) for the six key 5C predictors of default risk. (a) ALE-Income, (b) ALE-Household_debt, (c) ALE-Default_history, (d) ALE-Rrgular_saving , (e) ALE-External_1, and (f) ALE-External_2

Conclusion

This study demonstrates that developing a credit risk prediction model for agricultural cooperatives using quantitative data, Machine Learning (ML), and Explainable AI (XAI) has significant potential to enhance accuracy and adaptability in classifying high-risk borrowers. Prior research indicates that ML, particularly ensemble methodologies, frequently surpasses traditional statistical models, such as ordered-probit, especially in contexts characterized by incomplete or highly complex historical data (Ileberi, 2024; Gafsi, 2025). Nevertheless, the use of black-box machine learning models may pose challenges for transparency and trust among loan approval authorities and cooperative members, particularly when the model's decision-making logic is not understood. The application of Explainable AI (XAI), such as SHAP values, is therefore imperative for elucidating the reasoning behind risk-level assessments. Research conducted by Al Shiam *et al*. (2024) demonstrates that employing XAI can markedly enhance the transparency and credibility of machine learning-based credit decision systems.

Agricultural cooperatives operate within a unique context that differs from that of general commercial banks. This context is characterized by potentially incomplete member data, irregular income streams, diverse debt structures, and external influences such as commodity prices, weather conditions, and government policies (Chai *et al*., 2025). The implementation of robust machine learning and ensemble methods that address class imbalance and manage these complex datasets can significantly enhance model performance. For example, the use of a stacked classifier combined with feature selection and data balancing techniques has been shown to achieve an Area Under the Curve (AUC) of 0.934–0.944, thereby surpassing the performance of individual models (Ileberi, 2024). While ensemble models produce accurate results, the persistent trade-off between interpretability and precision remains. Sophisticated models such as XGBoost, Gradient Boosting, or Random Forest may lack transparency when explaining the specific criteria for credit approval or denial, especially when used with vulnerable borrowers or incomplete datasets (Gafsi, 2025).

Consequently, the deployment of Machine Learning (ML) and Explainable Artificial Intelligence (XAI) within cooperatives must be underpinned by strategic change management initiatives. These should encompass staff training, fostering a comprehensive understanding of the system's benefits, offering opportunities for employee engagement in workflow design, and restructuring debt monitoring processes (Al Shiam *et al*., 2024). Moreover, the quality of training data is of critical importance. If the data fails to include contextual variables such as raw material prices, weather conditions, or the economic state of the community, the model may be unable to generalize across different seasons or fluctuating economic conditions (Chai *et al*., 2025).

The research findings endorse the integration of the traditional 5Cs framework—employing a qualitative approach—with Machine Learning/Explainable Artificial Intelligence (ML/XAI)—a quantitative and data-driven methodology—serving as a hybrid strategy with substantial potential. ML/XAI tools enhance accuracy and processing efficiency when managing large data sets, whereas the 5Cs framework maintains qualitative components such as borrower reliability and external factors, which may not be fully captured by quantitative variables alone (Ileberi, 2024; Chai *et al*., 2025).

Policy Proposal: Agricultural cooperatives ought to implement risk forecasting systems employing machine learning, ensemble techniques, and explainable artificial intelligence (XAI) within their credit approval procedures. This strategy intends to improve accuracy, diminish non-performing loans (NPLs), and enhance transparency in decision-making. Additionally, it is essential to organize the change management process effectively by offering comprehensive training to personnel, cultivating a thorough understanding, and promoting active engagement in the development of workflows and the restructuring of debt collection processes.

The development of a comprehensive member data storage system that encompasses financial information and contextual factors such as seasonality, crop prices, debt burdens, and community economic conditions is crucial for enabling the model to generalize effectively. The implementation of Explainable AI (XAI) techniques, including SHAP, should be adopted to generate explanatory reports that clarify the decision-making processes of the model, thereby fostering understanding and acceptance among administrators and members of the cooperative (Al Shiam *et al*., 2024; Nallakaruppan *et al*., 2024). In conclusion, this research demonstrates that the application of machine learning (ML)/ensemble methods combined with explainable artificial intelligence (XAI) within agricultural cooperatives holds substantial promise (Gafsi, 2025; Chai *et al*., 2025). This potential is particularly notable in areas such as accuracy, transparency, and risk management (Rafi *et al*., 2024). Nevertheless, successful deployment necessitates meticulous system data design, organizational change management, and collaborative efforts across all sectors. When executed effectively, cooperatives can mitigate non-performing loans (NPLs), improve sustainable access to credit, and establish enduring financial stability for their members.

Limitations and Dimensions for Future Research

The study employed data obtained from questionnaires and secondary sources, with a sample size of n = 300. Such a sample may pose limitations concerning its representativeness of the cooperative member population nationwide. Additionally, processes such as the partitioning of training and test sets, cross-validation, management of class imbalance, variable selection, and pre-processing all impact the model's performance. The results may differ when real-world data is applied, as it often contains noise and demonstrates greater complexity.

Proposal for Future Research: Evaluate the hybrid model integrating machine learning (ML)/ensemble techniques, Explainable Artificial Intelligence (XAI), and the 5Cs framework to compare the effectiveness of qualitative and quantitative methodologies. Broaden the data collection scope to include cooperative members from multiple regions, seasons, and years, thereby enhancing the model's generalizability. Conduct a longitudinal study on the long-term implications of implementing ML/XAI within cooperative organizations, assessing impacts on Non-Performing Loans (NPLs), credit access, member satisfaction, employee acceptance, and systemic sustainability.

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