A model of 'Artificial Neural Network (ANN)' for IMF network classification: case of the UNACOOPEC-CI network in COTE D'IVOIRE (CI)

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The empirical study, conducted on the crates of the UNACOOPEC-CI network, has the advantage of using Artificial Neural Networks (ARN) in the preventive detection of crates in difficulty and of categorizing them. Thus, out of 124 cases selected, the neuron method classified 17 cases good and 107 bad. The method has an overall accuracy of 96.77%. This justifies the robustness of this method compared to the credit scoring method which in the literature, in general, has an accuracy of 72%.

Keywords: Microfinance; RNA; Microcredits; Credit scoring; UNACOOPEC-CI Network.

1. Introduction

Microfinance has generated considerable expectations and has become a central component of contemporary economic development dynamics. It concerns not only producers and financial actors, but also large professional and banking institutions as well as local initiatives in short, all stakeholders within an economy. Its primary merit undoubtedly lies in providing access to financial services to populations traditionally excluded from the formal banking sector.

Currently, formal financial institutions are increasingly incorporating lessons learned from experience in managing small-scale financial transactions. It is within this evolving landscape that the present research is situated. This study proposes the use of Artificial Neural Networks (ANNs) as innovative tools for preventing financial distress among cooperative credit unions within the UNACOOPEC-CI network.

Such innovations were introduced with the objective of reducing information asymmetries, transaction costs, and risk exposure (Meyer et al., 1999). Our research is grounded in contract theory, which posits that contractual incompleteness may lead to opportunistic behavior among borrowers (Ghatak and Guinnane, 1999). This theoretical framework evaluates credit performance from the perspective of the lending institution, focusing on poor households while simultaneously aiming to ensure the financial sustainability of microfinance institutions (MFIs). Within this perspective, financial self-sufficiency is regarded as a criterion that best fulfills the social mission of microfinance. More broadly, our approach adopts an institutionalist stance, consistent with Milton Friedman's view that profitability constitutes a fundamental condition for corporate responsibility.

Is lending to the poor financially viable? While the question may appear somewhat blunt, it nevertheless represents the core issue facing microfinance operators. Following an initial period of experimentation, the current challenge lies in institutional sustainability. Economies of scale and financial viability have thus become key principles guiding major development agencies, including the World Bank, USAID, the Consultative Group to Assist the Poor (CGAP), organizer of the Microcredit Summit, as well as large international NGOs such as Accion. This does not imply unanimity among practitioners—many continue to express reservations—but this approach has clearly become dominant, particularly under pressure from funding agencies.

Donors increasingly require programs to be financially sustainable, if not profitable. Consequently, even reluctant operators are compelled to align with these expectations. However, this strong emphasis on sustainability raises legitimate concerns: could it result in the exclusion of "non-profitable" clients? Historical developments in Western mutual and cooperative systems, as well as policy shifts observed in certain developing countries (Bennett and Cuevas, 1996), illustrate the relevance of this concern.

In this context, which predictive and classification tools can be employed to enhance the sustainability of MFIs within the UNACOOPEC-CI network? Rather than providing definitive answers, this study seeks to shed light on sustainability challenges by adopting a combined approach that simultaneously addresses risk exposure and the costs associated with growth—two inherently interrelated dimensions.

In the existing literature, Bolivia is frequently cited as a success story in microfinance. Similarly, the self-managed savings institutions of the Dogon region in Mali represent one of the most advanced experiences in solidarity-based finance in West Africa. Their operational model demonstrates that solidarity and financial viability are not mutually exclusive; indeed, solidarity mechanisms can offset the additional costs associated with challenging local contexts.

More broadly, microfinance in Latin America has progressively integrated into the formal financial sector while maintaining its commitment to financial inclusion and poverty reduction. Nevertheless, the absence of robust analytical, measurement, and monitoring frameworks within microfinance—compared to the more structured conventional banking system—raises critical questions. Does integration into formal financial systems risk diverting microfinance from its original mission? Could tensions arise between financial performance and social performance? Might the sustainability of this powerful development instrument be threatened by inadequate risk management? Furthermore, how can effective control of solvency risk become a driver of institutional performance?

In addressing these issues, we acknowledge that MFIs are permanently exposed to significant risks that may undermine not only their institutional sustainability but also the viability of financed projects and their socio-economic impact on target populations. Despite the existence of internal risk management and control mechanisms within the UNACOOPEC-CI network, this study re-examines the magnitude and nature of the risks faced, particularly in the context of institutional expansion.

The following research questions therefore guide our analysis: What specific risks does the UNACOOPEC-CI network face in relation to its growth trajectory? How effectively are mobilized resources managed within the network?

To answer these questions, we adopted an empirical methodology combining qualitative and quantitative approaches. Data were collected through semi-structured interviews and questionnaires administered to managers and officials of affiliated credit unions. Field visits were also conducted to capture local operational realities that are often less visible at higher administrative levels within the network. This mixed-method approach enables a comprehensive understanding of the institutional functioning, risk exposure, and governance mechanisms of the UNACOOPEC-CI network.

2. Context

Major headings should be typeset in boldface with the first letter of important words capitalized Microfinance has long been presented as a development financing mechanism aimed at compensating for the shortcomings of conventional financial systems in developing countries. Its emergence is closely linked to the adverse effects of structural adjustment programs imposed on developing economies following the global economic crisis of the 1980s. From a neoliberal perspective, particularly as promoted by institutions such as the World Bank, microfinance has been viewed as a tool for integrating poor populations into the global market economy by supporting informal microenterprises through microcredit schemes, managerial training, and technical capacity building, within a broader poverty reduction framework (Peemans, 2002, pp. 166–168).

However, the first generation of microfinance programs—primarily socially oriented and developed during the 1980s and 1990s under a subsidiarity logic—were characterized by high arrears rates and substantial operational costs. These weaknesses led to the progressive disappearance of many microcredit programs. By fostering a culture of non-repayment and lax management practices, these initiatives hindered the emergence of financially sustainable systems (Von Pischke, 1983, cited in Morduch, 2000, pp. 619–620). Moreover, poverty persisted in several regions despite a high concentration of microfinance activities.

This context of failure, observed in the early 2000s, prompted a shift toward the promotion of sustainable financial institutions as key instruments in the fight against poverty. This transition was accompanied by the development of “best practice” codes for microfinance institutions (MFIs) (Wampfler & Roesch, 2004, pp. 249–267). Methodologically, the literature evolved along two main lines: one focusing on impact assessment and the other on organizational diagnosis (Labie, 2004, p. 19; Zeller, Lapenu & Greeley, 2004).

The present article is situated within this second methodological approach, emphasizing the sustainability of microfinance organizations in Côte d'Ivoire. Over the past decade, the microfinance sector has gained increasing importance as a poverty reduction tool in the country. Since the political crisis that began in 1999, which severely deteriorated socio-economic conditions, a growing share of the population has turned to income-generating activities. Microfinance institutions that emerged in this context were initially almost exclusively driven by a social mission and did not prioritize financial profitability.

However, the numerous bankruptcies that have marked the sector triggered a structural transformation. The sector gradually evolved from a purely socially oriented model toward one seeking to reconcile social outreach with financial viability. While the number of active microfinance organizations continues to increase, so too does the number of institutional failures, resulting in the loss of small savers' funds and undermining public confidence in the financial system.

The microfinance sector therefore presents a dual challenge for practitioners, public authorities, and development partners: not only to expand access to financial services for underserved populations but also to ensure the long-term sustainability of these services. The commitment to institutionalizing sustainable microfinance practices led to the adoption of a National Microfinance Policy, which entered into force in July 2006. Its objective is to "contribute sustainably to the improvement of living conditions of populations excluded from the conventional banking system and to increase their incomes through the provision of durable, high-quality financial products and services" (UNDP, 2004, p. 10).

Nevertheless, the implementation of such policies often faces structural and organizational constraints, particularly due to local operational realities that remain difficult to observe and manage from the higher levels of administrative hierarchy within microfinance networks.

2.1. *Research Objectives*

The primary objective of this study is to stimulate interest in the application of Artificial Neural Networks (ANNs) in microfinance, particularly for the early detection of distressed microfinance institutions and for their classification as a means of enhancing institutional sustainability. In other words, this research seeks to assess the relevance and effectiveness of ANN-based systems within the microfinance sector.

Furthermore, the study aims to contribute to the existing literature on solvency risk management in microfinance institutions (MFIs), with a specific focus on the Ivorian context.

The following specific objectives are also pursued:

- To significantly reduce the risk of permanent capital loss,
- To improve liquidity risk management,

- To establish conditions conducive to more efficient and performance-oriented institutional management,
- To develop a management quality indicator capable of supporting supervisory and strategic decision-making.

3. Selected Studies Applying Artificial Neural Networks to Classification Problems

Artificial Neural Networks (ANNs) emerged in the 1990s as a prominent methodological approach in finance, particularly for classification-related problems such as corporate distress detection, portfolio management (Paquet & Ambler, 1997), exchange rate forecasting, asset valuation (Bolgot & Meyfredi, 1999), and strategic decision-making (Smith & Di Gregorio, 2002).

Odom and Sharda (1990) argue that ANNs outperform traditional statistical techniques in classification tasks. In their empirical study, the neural network model yielded superior predictive performance compared to discriminant analysis on a test sample. Specifically, the ANN correctly classified 81.81% of firms, whereas discriminant analysis achieved an accuracy rate of 74.28%. They conclude that neural networks provide a more reliable framework for corporate classification problems.

In the same vein, Tam and Kiang (1992), following an in-depth comparative analysis, demonstrate that inductive learning systems namely ANNs are more effective than discriminant analysis in predicting corporate bankruptcy and loan default.

Extending this line of inquiry to bankruptcy forecasting, Coats and Fant (1992) suggest that both discriminant analysis and neural network models can achieve satisfactory classification performance when the classification problem is relatively well-structured. However, they strongly emphasize that neural networks exhibit superior performance when misclassification types and associated error costs are explicitly taken into account. This advantage highlights the robustness of ANNs in decision-making contexts where asymmetric error costs are economically significant.

4. Justification of the Methodological Choice

Several methodological frameworks have been developed to assess and diagnose Microfinance Institutions (MFIs) (Labie, 2004). Among the most widely recognized and frequently applied approaches are the PEARLS, CAMEL, and GIRAFE methodologies. In addition, specialized institutions have designed comprehensive evaluation tools, including the CGAP appraisal guide, the technical guide entitled Performance Indicators for Microfinance Institutions developed by MicroRate and the Inter-American Development Bank (IDB), as well as the performance criteria elaborated under the USAID Microenterprise Innovation Project.

Each evaluation framework has a specific scope of application and relies on particular assessment criteria and analytical instruments—such as performance indicators, financial ratios, dashboards, and econometric models—depending on the strategic priorities emphasized (e.g., sustainability, effectiveness, efficiency, outreach, or impact).

In this study, our focus is placed on analytical tools suitable for measuring solvency risk from an operational perspective, specifically through the assessment of the two principal risk categories affecting MFIs: credit risk and fraud risk.

To evaluate solvency risk, we adopt Artificial Neural Networks (ANNs) as our primary methodological framework. The theoretical foundation of ANNs highlights their ability to address unstructured problems, namely situations where little or no prior information is available. Notably, ANNs do not require prior assumptions regarding the probability distribution of variables, unlike most conventional statistical models—except in the case of non-parametric approaches. By autonomously identifying underlying relationships among variables, ANNs are particularly well-suited for modeling highly complex and nonlinear phenomena.

This feature is especially valuable, as it eliminates the need to pre-specify the functional form of the relationship to be estimated. Furthermore, ANNs demonstrate robustness when handling incomplete or noisy datasets. Data incompleteness can be accommodated through the integration of additional neurons within the network architecture. Casta and Prat (1994) show that specifically designed architectures aimed at addressing missing data issues can significantly enhance the predictive performance of early warning models for firms in financial distress.

Since the early 1990s, financial applications of Artificial Neural Networks have expanded considerably. Broadly speaking, these applications fall into three main categories: time-series forecasting, expert system substitution, and classification tasks. From a theoretical standpoint, ANNs are widely recognized as outperforming traditional classification techniques in terms of predictive accuracy and flexibility, particularly in complex decision-making environments characterized by nonlinear interactions and informational asymmetries.

4.1. *Data Collection Process*

A preliminary survey was conducted with UNACOOPEC-CI, the umbrella organization of the cooperative savings and credit institutions (COOPECs) in Côte d'Ivoire. This pilot phase enabled us to refine and adapt both the questionnaire and the interview guide to the specific operational realities of the microfinance sector.

The finalized questionnaire was subsequently transmitted electronically to the headquarters of UNACOOPEC-CI, whose management agreed to disseminate it through the institution's intranet system in order to collect the information required for this study from all affiliated units (134 cooperative branches distributed across the entire Ivorian territory).

Regarding the qualitative component, data were collected through semi-structured interviews conducted with senior executives and operational managers, including the provisional administrator of UNACOOPEC-CI, the Director of Administrative and Financial Affairs, the Regional Directors for the Western and Northern zones, as well as 51 branch managers (11 in the North, 7 in the South-East, 9 in the Centre-West, 20 in the South, and 4 in the West). In addition, 13 telephone interviews were conducted with credit officers from various branches within the UNACOOPEC-CI network. Institutional site visits were also carried out to enhance contextual understanding.

The interviews covered a wide range of topics, including the different types of credit products, general credit policy, default risk prevention mechanisms, refinancing conditions, risk measurement indicators, and collateral requirements.

Quantitative analysis was performed using institutional data collected from annual activity reports, balance sheets, income statements, financial statements, and centralized data collection forms provided by the network. These documents enabled the construction of a comprehensive dataset suitable for subsequent empirical analysis.

4.2. *Empirical Conceptual Model of the Artificial Neural Network Employed*

The artificial neural network (ANN) model adopted in this study is conceptually structured as follows:

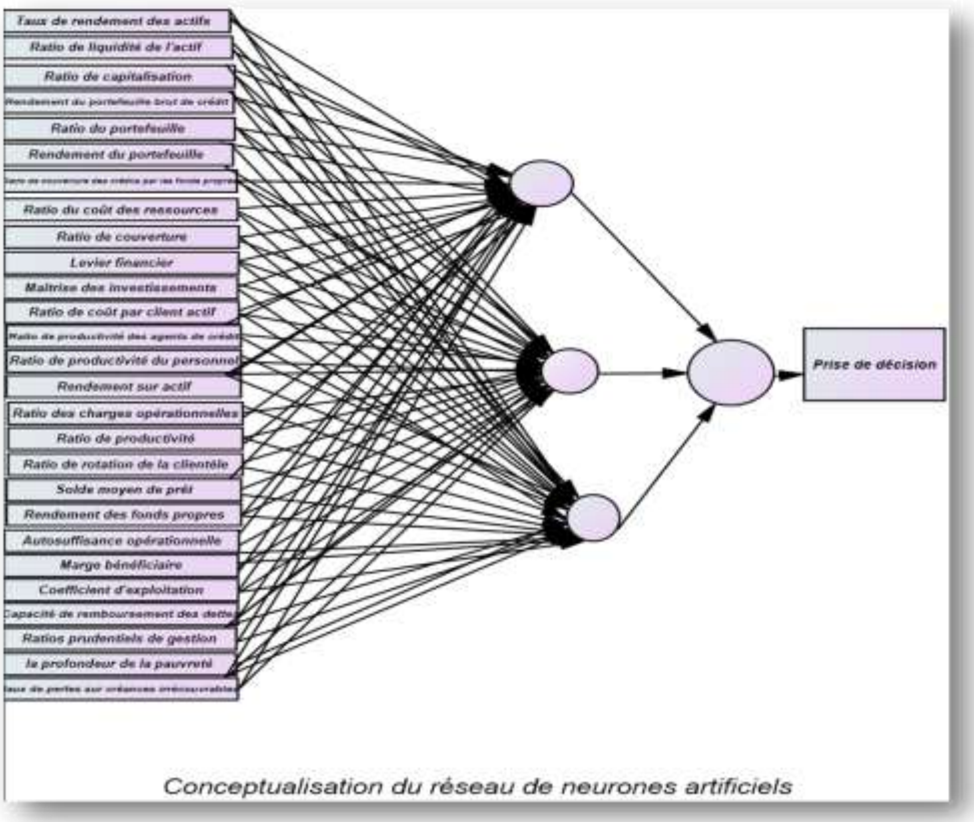

Fig. 1. The author

5. Results of the Neural Network Analysis

The variable IQGB, which captures the managerial quality of the microfinance institutions (MFIs) in our dataset, is constructed as follows.

First, we compute the average level of managerial quality across all institutions prior to data imputation. Next, for each individual institution, its managerial quality index (IQG_i) is compared with the overall mean managerial quality level.
Let $\overline{IQG}$ denote the average managerial quality level of the institutions, and $IQGi$ IQGi the managerial quality of institution.
if $\mathrm{IQG}_i > \overline{\mathrm{IQG}}$ then the binary variable IQGB takes the value 1;
if $\mathrm{IQG}_i < \overline{\mathrm{IQG}}$ then IQGB takes the value 0.
Thus, IQGB serves as a dichotomous classification variable distinguishing institutions with above-average managerial quality from those below the sample mean.

Table 1: Classification of Institutions by Management Quality

IQGB	EFFECTIFS	POURCENTAGES
MAUVAISE QUALITE DE GESTION	107	86,29%
BONNE QUALITE DE GESTION	17	13,71%
TOTAL	124	100%

Source: Author's calculations using STATA 13.

The best-managed institutions, exhibiting strong managerial dynamism and performance quality, are ranked from the highest to the lowest level of efficiency. They account for 17 out of the 124 institutions included in the sample. Paradoxically, only six (6) of these institutions are formally accredited, representing 35.29% of the best-performing group. This finding suggests that accredited institutions appear to have a lower probability of demonstrating strong managerial performance compared to non-accredited institutions. Indeed, non-accredited institutions represent 64.70% of the high-performing group. In other words, non-accredited institutions tend to exhibit comparatively stronger management quality and performance outcomes.

Table 2: Summarise the names and legal statuses of the various microfinance institutions that demonstrate strong operational performance and high managerial quality

	REGION	COOPEC	STATUT
2	ABIDJAN	Abobo	Non agréée
5	ABIDJAN	Adjamé	Non agréée
7	ABIDJAN	Plateau	Non agréée
8	ABIDJAN	Treichville	Non agréée
9	ABIDJAN	Cocody	Agréée
10	ABIDJAN	Angré	Non agréée
13	ABIDJAN	Riviera Ste F.	Non agréée
16	ABIDJAN	Koumassi	Non agréée
18	ABIDJAN	Port-Bouet	Non agréée
19	ABIDJAN	Yop Selmer	Agréée
20	ABIDJAN	Yop Ananeraie	Non agréée
22	ABIDJAN	Yop Keneya	Non agréée
24	ABIDJAN	Yop Toit Rouge	Non agréée
30	TOUMODI	Yamoussoukro	Agréée
73	DALOA	Daloa	Agréée
91	GAGNOA	Gagnoa	Agréée
112	SAN PEDRO	San-Pédro	Agréée

Source: Author's calculations using STATA 13.

In summary, the final results of ranking the cash offices using the artificial neural network method are as follows. Out of 124 cash offices to be classified, the neural network method correctly ranked 120 offices, yielding an overall accuracy of 96.77%. Only four offices were misclassified. The method demonstrates even higher precision for poorly performing offices, achieving an accuracy of 99.05% for this category. In other words, it is more difficult for a poorly performing office to be misclassified as a good one than for a good office to be classified among the poorly performing offices, as evidenced by an accuracy of 84.21% for the well-performing offices. Specifically, among the 107 poorly performing offices, only one was mistakenly classified as good, whereas among the 17 well-performing offices, three were incorrectly assigned to the poorly performing category. These results highlight the robustness of the neural network method compared to traditional credit scoring approaches, which, according to the literature, typically achieve an overall accuracy of around 72%.

Table 3: Results of the Neural Network Method

POURCENTAGE DE BIEN CLASSES

	BIEN CLASSES	MAL CLASSES	TOTAL	%BIEN CLASSES	PURETE
C103=0	104	3	107	97.20	99.05
C103=1	16	1	17	94.12	84.21
TOTAL	120	4	124	96.77	96.77

Source: The author

6. Discussion

A comparative analysis between discriminant analysis and neural network approaches was conducted, as the former remains the most widely used method in general, and particularly in Côte d'Ivoire. The comparison of these two methods is presented through the results reported in several studies. Indeed, numerous investigations have sought to demonstrate the effectiveness of one approach over the other.

Odom and Sharda (1990) reported that neural networks outperform traditional statistical methods. The neural network employed in their study produced better results than discriminant analysis on the test sample. Similarly, Coats and Fant (1992), in the context of corporate bankruptcy prediction, recommended the use of both discriminant analysis and neural networks if the user's primary objective is to achieve correct classification, while emphasizing that neural networks outperform discriminant analysis when considering the type of error committed and the associated cost.

In contrast, Swales and Yoon (1992) argued that the simultaneous application of neural network methods and discriminant analysis is rather difficult under current testing frameworks, as the two methods rely on fundamentally different theoretical foundations. However, combining neural networks with discriminant analysis yields the best results, as demonstrated by Altman et al. (1994) in their study of 1,000 Italian industrial firms between 1982 and 1992. Angelini et al. (2014) observed that the neural network approach differs from the traditional credit scoring method mainly due to the "black box" nature of the model and its capacity to handle nonlinear relationships between variables. In general, according to these authors, neural networks are considered black boxes because it is impossible to extract symbolic information from their internal configuration. Indeed, the neural network correctly classified 81.81% of firms compared to 74.28% using discriminant analysis.

Conversely, Hoang (2000), in his doctoral dissertation, asserted that discriminant analysis methods can achieve better performance than neural networks when linear patterns are involved in the classification task, whereas neural networks are more capable of detecting nonlinear patterns.

In the context of credit risk forecasting, Abdou et al. (2007) conducted a comparative analysis between neural networks and discriminant analysis. The study sample, provided by a commercial bank in Egypt, comprised 581 credit files. The individuals in the sample were classified into two groups: financially healthy firms (1) and financially distressed firms (0). An initial set of 20 independent variables was selected by the bank; however, several variables exhibited identical values across the sample (e.g., the loan duration was four years in all cases, and all clients possessed a credit card), and were therefore excluded. Consequently, the selected variables were reduced to 12, which were used for discriminant analysis. This model correctly classified 86.75% of firms.

Using this same set of 12 variables, the authors applied a stepwise regression method, which identified nine variables with significant discriminatory power. These variables were subsequently used in discriminant analysis, achieving a correct classification rate of 86.92%. Abdou et al. (2007) retained all 12 variables to construct the neural network model. Results showed a correct classification rate of 93.98% using a neural network with four hidden nodes, and 94.84% using a network with five hidden nodes. The authors concluded that the neural network approach outperforms discriminant analysis, as it achieves the highest correct classification rate.

7. Conclusion

This study contributes to the field of artificial intelligence by applying Artificial Neural Networks (ANNs) as a viable alternative to traditional statistical methods in the development of a Management Quality Indicator (MQI) for classifying microfinance institutions (MFIs) within a network. Specifically, a feedforward multilayer perceptron (MLP) comprising successive layers was employed on a sample of 124 MFIs from the UNACOOPEC-CI network for this analysis.

The results indicate that 17 institutions out of the 124 exhibit good management quality. Paradoxically, six (6) licensed institutions, representing only 35.29% of the best-performing institutions, were among these top performers. In other words, a licensed institution is less likely to demonstrate high management quality and strong performance compared to an unlicensed one. The unlicensed institutions constitute 64.70% of the best-performing institutions, suggesting that unlicensed MFIs can achieve a high level of management quality.

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