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Analytical Hierarchy Process as a Priority Strategy for Handling Bad Debts in Cooperatives

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ABSTRACT: The Kediri City Government and the Regional Development Planning Agency are committed to accelerating the economic recovery of the Kediri city community after the impact of the Covid-19 pandemic, by focusing on MSME capital, the program named *Kredit Usaha Melayani Warga* or abbreviated as KOPERASI provides very low interest loans of 2% per year for business people in Kediri city. In the utilization of this credit, it turns out that there are still bottlenecks in installments, which if allowed to continue, will have an impact on financial losses and also not achieve the goal of community economic recovery. So that the government needs an in-depth study as a real form of handling bad credit and also the concept of effective and efficient KOPERASI program governance. This research uses a quantitative descriptive approach, by applying the Analytical Hierarchy Process (AHP) method. Starting from making questionnaires and determining respondents. The respondents selected were 7 experts, namely, officials at the Kediri City Cooperative & UMTK Office, lecturers at the Faculty of Economics, Universitas Nusantara PGRI Kediri, and MSME beneficiaries of the KOPERASI program. Then the answers are assessed and compared to produce a scale as a determination of the most effective method of overcoming bad credit.

KEYWORDS: AHP, Bad debts, Koperasi.

INTRODUCTION

Bad debts are one of the main challenges faced by the financial sector, including cooperatives. Effective handling of bad debts requires appropriate strategies and is supported by effective management. Bad debts have been a major focus in finance and management literature for decades. As one of the biggest challenges faced by the financial sector, including cooperatives, bad debts affect not only the welfare of financial institutions, but also the overall macroeconomic stability (Fakhrunnas, 2019). In the context of cooperatives, bad debts can affect member confidence, reduce funding sources, and ultimately threaten the viability of the cooperative itself.

Handling bad debts is not a simple task. It requires an appropriate strategy that is based on an in-depth understanding of the factors that influence the occurrence of bad debts and how to overcome their negative impact. Some of the major factors affecting bad debts include macroeconomic conditions, such as inflation rates and GDP growth, as well as internal factors such as lending policies, management competencies, and cooperative governance structures (Dewi & Purwono, 2020). In addition, the presence of effective management is a key factor in handling bad debts. Without proper policies and procedures, as well as a good understanding of the risks involved, a cooperative can easily find itself in a situation where the number of bad debts increases rapidly, threatening the institution's solvency and reputation (Podpiera & Ötker, 2010).

However, in the context of cooperatives, there are unique challenges in handling bad debts. For example, decisions in cooperatives are often made based on the consensus of members, who may have different views and interests. Therefore, there is a need for methods that can assist cooperatives in making objective and systematic decisions. One method that shows promise in supporting complex decision-making is the Analytical Hierarchy Process (AHP). AHP is a technique that allows decision makers to decompose complex problems into simpler components and evaluate alternatives based on predetermined criteria (de Oliveira et al., 2023). Through this approach, AHP can assist cooperatives in prioritizing and selecting bad debt handling strategies that best suit their needs and conditions.

The application of AHP in the context of bad debts has not been widely explored, especially in a cooperative setting. However, its potential to improve management effectiveness in handling bad debts is something that deserves further investigation. By utilizing

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AHP, it is hoped that cooperatives can make more informed and objective decisions, reduce the risk of bad debts, and ultimately improve the welfare of their members.

LITERATURE REVIEW

A. Lending Management

Credit management is considered to be the most important action for any business that cannot be ignored by any financial company. Credit management states the process of extending credit to customers with a repayment term that allows the terms to pay the maturity on time with full payment (Shyam Narain, 2022). The management of lending is changing more and more dynamically, especially now that corporate credit risk during the covid19 pandemic has also continued to fluctuate. More specifically, using a dynamic rating transition model, it was found that augmenting credit risk simulations with further stress tests made risk quantiles very conservative compared to realized risk, even during stressful times such as the pandemic (Telg et al., 2023). Good credit management promotes the financial stability of the business with continued profitability in the business. With good credit management, receivables risk is minimized, and business growth opportunities are increased. A good credit management plan formulates a continuous and proactive process of identifying risks by evaluating possible losses and deliberately guarding against lending risks. A good credit management plan helps protect the cash flow of the business by optimizing performance and reducing the likelihood of defaults that will affect the business. More than half of bankruptcies are caused by poor credit management. Even profitable businesses turn into losses if their receivables are not managed properly. With improper working capital or less than needed to pay off creditors and other expenses, a business can quickly get into debt.

B. Credit risk assessment

Credit risk, especially financial credit, denotes the risk associated with financing, in other words, the borrower being unable to repay the lender, or defaulting. As such, financial credit risk assessment intends to solve the problem stated as follows: Given a set of companies labeled as bad/good credit or insolvent/healthy, and a set of financial variables describing the company's situation during a given period, predict the probability that the company may fall into the high-risk group or become insolvent during the following years. The former problem is called credit rating or valuation, and the latter problem is called bankruptcy (failure) prediction or forecasting of a company's financial difficulties. Both are solved in the same way as a binary classification task (Chen et al., 2016).

The earliest research on financial credit risk assessment can be traced to (FitzPatrick, 1932) and the famous Altman model (1968). To date a wide variety of approaches have been used to evaluate creditworthiness using traditional statistical methods or advanced machine learning methods. A great deal of evidence has been found in recent studies showing that intelligent methods can markedly improve the accuracy of statistical methods without relying on restrictive assumptions. These techniques include artificial neural networks (ANN), fuzzy set theory (FST), decision trees (DT), case-based reasoning (CBR), support vector machines (SVM), rough set theory (RST), genetic programming (GP), hybrid learning, and ensemble computing among others. The earliest research on financial credit risk assessment can be traced to FitzPatrick On the other hand, a general conclusion was reached that no method outperforms all others consistently across different data sets. Early reviews in the accounting and finance domain focused on statistical-based models (Dimitras et al., 1996; Hand & Henley, 1997). Subsequent machine learning techniques were extensively studied with more attention. An exhaustive review (Bellovary et al., 2007) traces a summary history of bankruptcy prediction studies and introduces trends in this area. In another study, Ravi Kumar & Ravi, (2007) reviewed statistical and intelligent techniques of bankruptcy prediction in banks and corporations. Lin et al. reviewed the development of advanced machine learning techniques for bankruptcy prediction and credit scoring from 1995 to 2010 (Lin et al., 2012). Some researchers also highlighted specialized learning models as a hot topic and promising trend in review articles. For example, Verikas et al. (2010) surveyed hybrid and ensemble techniques able to improve the accuracy of corporate bankruptcy prediction, Woźniak et al. (2014) discussed approaches to build a multiple classifier system Jayanthi et al. (2011) reported the application of SVM and hybrid SVM for bankruptcy prediction, and Brabazon et al. (2011) introduced the application of neural computing to widespread financial problems. Some studies are limited to the development of NN techniques (Brabazon et al., 2011; Calderon & Cheh, 2002; Nazareth & Ramana Reddy, 2023; Vellido et al., 1999; Wong et al., 1997). With the magnitude of prediction models increasing in recent years, there is a need to review recent research on

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METHOD

This research uses a quantitative descriptive approach, by applying the Analytical Hierarchy Process (AHP) method. The use of this method aims to determine strategies for handling bad debts and the effectiveness of cooperative management. The following are the stages in the implementation of the AHP method.

A. Compilation of Questionnaires and Respondents

The questionnaire aims to capture respondents' perceptions as experts to generate primary data. The use of this questionnaire was chosen because the consensus method, namely by gathering respondents together in the same place and time, is very difficult to do. Respondents were selected based on their professionalism, active participation in policy planning, and knowledge and understanding of the issues being studied. Determining the number of experts required as respondents to provide an assessment on the AHP questionnaire is actually very relative. One person who really understands the problem may give better results than the assessment of many respondents who do not really understand the problem. However, if there are too few respondents, and if the assessment is biased, then the overall analysis results will be poor. To avoid this, the number of experts chosen is not too small, so that if there is a rather odd assessment, it can be neutralized by the average assessment of a number of experts. In this study, the experts who were asked to be respondents to the AHP questionnaire were 5 people, namely, the management of the Kediri City Cooperative, lecturers at the Faculty of Economics, Universitas Nusantara PGRI Kediri, and MSME beneficiaries of the KOPERASI program.

B. AHP Questionnaire Assessment

Respondents' assessment of the AHP questionnaire was carried out by providing an assessment from a scale of 1 to 9, with an explanation as in the following table:

Scale	Meaning	Description
1	Both elements are of equal importance	The two elements being compared contribute equally to achieving the goal
3	One element is slightly more important than the other (moderate importance)	Experience and judgment slightly favor one element over another
5	One element is more important than the other (essential/strong importance)	Experience and judgment more strongly favor one element over another
7	One element is very much more important than the other (very strong importance)	One element is strongly favored over the other, its dominance being apparent in the actual situation
9	One element is absolutely more important than the other (extreme importance)	An absolute element is more strongly favored than others and is at the highest level
2,4,6,8	Is a compromise number between the above assessments	When a compromise is required between two considerations/judgments

RESULT AND DISCUSSION

To effectively manage credit handling using the Analytical Hierarchy Process (AHP) method, we can develop 3 Strategies, 4 Focus Areas, and 5 Alternatives. AHP will help in making more structured and systematic decisions by comparing these elements in pairs based on their priority. Here are the details: The following are the steps taken in applying the Analytical Hierarchy Process (AHP) method.

Define the problem and determine the desired solution, namely

1. The selection of bad credit handling policy strategies includes: Increasing the Efficiency of Credit Management, Reducing Credit Risk, Innovating Credit Products and Services.
2. Determination of the selection focus on the following areas: Credit Analysis and Assessment, Risk Management and Policy, Borrower Education and Awareness, Credit Monitoring and Collection.

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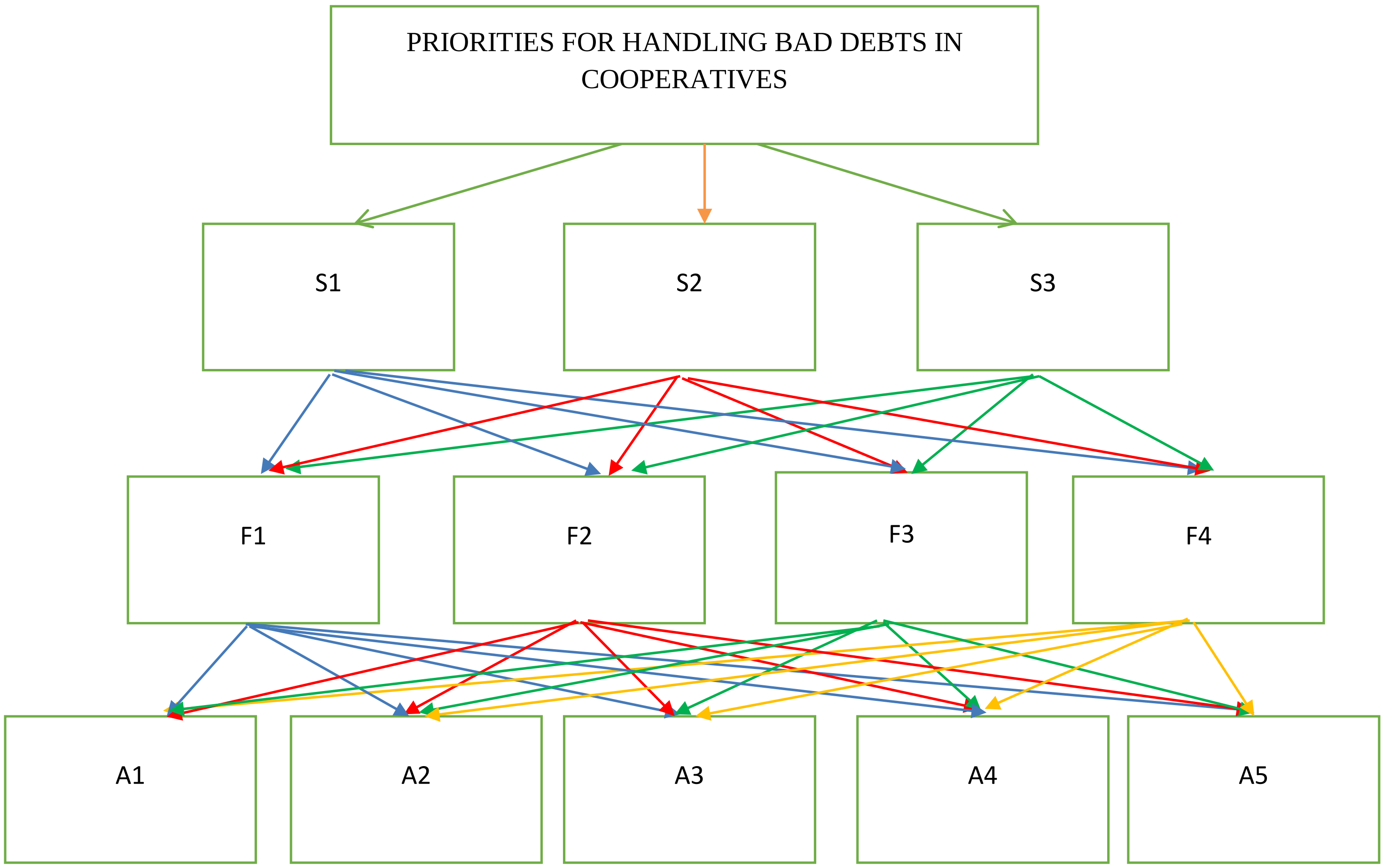
3. Determination of preferred alternatives: Borrower Financial Criteria, Credit Guarantee and Security, Socio-Economic Impact of Credit, Regulatory Compliance and Internal Policies, Technology and Innovation in Credit Processes
4. Create a hierarchical structure that begins with the general objective, followed by a focus on areas according to the criteria and possible alternatives at the lowest level.



Description of coding

Strategy	:	Improved Credit Management Efficiency	:	S1
	:	Credit Risk Reduction	:	S2
	:	Innovation of Credit Products and Services	:	S3
Field of Focus	:	Credit Analysis and Assessment	:	F1
	:	Risk Management and Policy	:	F2
	:	Borrower Education and Awareness	:	F3
	:	Credit Monitoring and Collection	:	F4
Alternatives	:	Borrower Financial Criteria	:	A1
	:	Credit Guarantee and Security	:	A2
	:	Socio - Economic Impact of Credit	:	A3
	:	Regulatory Compliance and Internal Policies	:	A4
	:	Technology and Innovation in Credit Process	:	A5

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Create a pairwise comparison matrix to illustrate the contribution of the influence of each element to each of the objectives or areas that are at the same level above. Comparisons are made based on the "judgment" of all respondents by rating the importance of an element compared to other elements.

Table 1. Pairwise comparison mapping for strategy elements

Strategy	S1	S2	S3
S1	1,000	3,000	6,000
S2	0,333	1,000	4,000
S3	0,167	0,250	1,000
Amount	1,500	4,250	11,000

Table 2 Calculating Eigen Vectors

Strategy	S1	S2	S3	Amount	Priority
S1	0,667	0,706	0,545	**1,918**	**1**
S2	0,222	0,235	0,364	0,821	2
S3	0,111	0,059	0,091	0,261	3
AMOUNT	1	1	1	3,000	

From table 2 above, it can be determined that the Credit Management Efficiency Improvement strategy is a priority compared to the Credit Risk Reduction and Credit Product and Service Innovation strategies. Priority calculations for focus areas are carried out on all strategies.

Table 3. Pairwise comparison mapping for Credit Management Efficiency Improvement with each focus area

Field of Focus	F1	F2	F3	F4
F1	1,000	5,000	0,333	3,000
F2	0,200	1,000	3,000	0,250
F3	3,000	0,333	1,000	0,500
F4	0,333	4,000	2,000	1,000
Amount	4,533	10,333	6,333	4,750

Table 4. Calculated the eigenvectors for pairwise comparisons for the strategy of Improving Credit Management Efficiency with each focus area

Field of Focus	F1	F2	F3	F4	Eigen Vector	Priority
F1	0,221	0,484	0,053	0,632	**1,389**	**1**
F2	0,044	0,097	0,474	0,053	0,667	4
F3	0,662	0,032	0,158	0,105	0,957	3
F4	0,074	0,387	0,316	0,211	0,987	2
Amount	1	1	1	1	4	

Table 4 shows that in the strategy of Improving Credit Management Efficiency, Focus Area 1 (F1) has the highest eigenvector value (1.389), indicating that this is the most important focus area in the context of the strategy of Improving Credit Management Efficiency. Focus Area 4 (F4) has the second priority (0.987), followed by Focus Area 3 (F3) with an eigenvector value of 0.957, placing them in the second and third positions. Focus Area 2 (F2) shows the lowest priority with an eigenvalue of 0.667. From this

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analysis, it can be concluded that F1 is the most critical area and should be the main focus in the Credit Management Efficiency Improvement strategy. Focus on F4 and F3 are also important, but with lower priority than F1. F2, despite its contribution, is the lowest priority among the four focus areas.

Table 5. Pairwise comparison mapping for Credit Risk Reduction strategies with each focus area

Field of Focus	F1	F2	F3	F4
F1	1,000	0,500	2,000	5,000
F2	2,000	1,000	6,000	4,000
F3	0,500	0,167	1,000	3,000
F4	0,200	0,250	0,333	1,000
Amount	3,700	1,917	9,333	13,000

Table 6. Calculated the eigenvectors for pairwise comparisons for Credit Risk Reduction strategies with each focus area

Field of Focus	F1	F2	F3	F4	Eigen Vector	Priority
F1	0,270	0,261	0,214	0,385	1,130	2
F2	0,541	0,522	0,643	0,308	**2,013**	**1**
F3	0,135	0,087	0,107	0,231	0,560	3
F4	0,054	0,130	0,036	0,077	0,297	4
Amount	1,000	1,000	1,000	1,000	4,000	

Table 6 shows that Focus Area 2 (F2) has the highest eigenvector value (2.013), placing it at the first priority. This indicates that F2 is the most important aspect of a credit risk reduction strategy. F2 may include elements such as strict risk assessment policies or advanced technology for early risk detection. Focus Area 1 (F1), with an eigenvalue vector of 1.130, is placed at the second priority. This indicates that F1 also plays an important role in this strategy, but not as much as F2.

Table 7. Pairwise comparison mapping for Credit Product and Service Innovation strategy with each focus area

Field of Focus	F1	F2	F3	F4
F1	1,000	0,143	4,000	0,500
F2	7,000	1,000	5,000	3,000
F3	0,250	0,200	1,000	0,333
F4	2,000	0,333	3,000	1,000
Amount	10,250	1,676	13,000	4,833

Table 8. Calculated the eigenvectors for pairwise comparisons for Credit Product and Service Innovation with each focus area

Field of Focus	F1	F2	F3	F4	Eigen Vector	Priority
F1	0,098	0,085	0,308	0,103	0,594	3
F2	0,683	0,597	0,385	0,621	**2,285**	**1**
F3	0,024	0,119	0,077	0,069	0,290	4
F4	0,195	0,199	0,231	0,207	0,832	2
Amount	1,000	1,000	1,000	1,000	4,000	

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Based on the data above, it appears that for the strategy option of Improving Credit Management Efficiency, the focus area is on Credit Analysis and Assessment (F1), while for the Credit Risk Reduction strategy and the Credit Product and Service Innovation strategy, the focus area is Risk Management and Policy.

Table 9. Determine the strategy and focus of priority areas

Strategy	**S1**	**S2**	**S3**		
Field of Focus	1,918	0,821	0,261	**Eigen Value**	**Priority**
F1	**1,389**	1,130	0,594	**3,746**	**1**
F2	0,667	**2,013**	**2,285**	3,529	2
F3	0,957	0,560	0,290	2,371	3
F4	0,987	0,297	0,832	2,354	4

Table 9 presents the results of calculations to prioritize strategies and focus areas using the Analytical Hierarchy Process (AHP) method. This table integrates three strategies, namely Improving Credit Management Efficiency (S1), Reducing Credit Risk (S2), and Innovating Credit Products and Services (S3), and examines four focus areas: Credit Analysis and Assessment (F1), Risk Management and Policy (F2), Borrower Education and Awareness (F3), and Credit Monitoring and Collection (F4).

Table 9 also shows that each strategy was assessed based on its contribution to the four focus areas. The eigenvalues obtained reflect the relative importance of each strategy in the overall context. For an explanation of the Focus Areas Calculation and Assessment is as follows:

The values listed for F1, F2, F3, and F4 indicate their valuation in the context of each strategy. The total eigenvalue for each focus area is calculated to determine their overall priority.

Based on table 9, it is also known regarding the Prioritization of Focus Areas, namely:

1. Focus Area 1 (F1) - Credit Analysis and Assessment: With the highest total eigenvalue (3.746), F1 is the most important focus area. This indicates that credit analysis and assessment is a key area in improving credit management efficiency, credit risk reduction, and product and service innovation.
2. Focus Area 2 (F2) - Risk Management and Policy: With a total eigenvalue of 3.529, F2 is the second priority. It emphasizes the importance of risk management and policies, especially in the context of credit risk reduction and product innovation.
3. Focus Area 3 (F3) - Borrower Education and Awareness: With an eigenvalue of 2.371, F3 is the third priority, indicating the importance of borrower education and awareness albeit with a smaller contribution than F1 and F2.
4. Focus Area 4 (F4) - Loan Monitoring and Collection: With the lowest score (2.354), F4 has the last priority, indicating that although important, loan monitoring and collection is not as prioritized as other areas in the context of the strategy set.

These results suggest that the main focus should be on credit analysis and assessment (F1), followed by risk management and policies (F2). Borrower education and credit monitoring are also important but of lower priority. This approach allows for a more effective and focused allocation of resources to achieve strategic objectives in credit management.

Priority calculation for all alternatives against all focus areas

Table 10. Recapitulation of eigenvectors from pairwise comparisons of focus areas and policy alternatives

Field of Focus	**F1**	**F2**	**F3**	**F4**	**Eigen Value**	**Priority**
Alternative	**3,746**	3,529	2,371	2,354		
A1	0,733	2,250	0,849	2,311	18,138	2
A2	1,642	0,690	0,696	1,512	13,796	3
A3	0,436	0,362	0,372	0,127	4,092	5
A4	0,366	0,411	0,526	0,140	4,398	4
A5	1,823	1,287	2,557	0,910	**19,576**	**1**

Table 10 provides a comprehensive analysis using the Analytical Hierarchy Process (AHP) method to evaluate a number of policy alternatives related to four different focus areas: Credit Analysis and Appraisal (F1), Risk Management and Policies (F2), Borrower Education and Awareness (F3), and Credit Monitoring and Collection (F4). The five policy alternatives evaluated were Borrower Financial Criteria (A1), Credit Guarantee and Security (A2), Socio-Economic Impact of Credit (A3), Regulatory Compliance and Internal Policies (A4), and Technology and Innovation in the Credit Process (A5).

Each policy alternative is assessed based on its contribution to the four focus areas. The eigenvalues shown in the table illustrate the relative importance of each alternative in the overall context. Technology and Innovation in Credit Process (A5) has the highest eigenvalue (19.576), placing it at the first priority. This indicates that technological innovation is considered the most critical factor in improving performance in all focus areas. For Borrower Financial Criteria (A1), it is the second priority with an eigenvalue of 18.138, signifying the importance of borrower financial analysis in all aspects of credit management. Credit Guarantee and Security (A2) has an eigenvalue of 13.796, placing it at the third priority. Regulatory Compliance and Internal Policies (A4) and Socio-Economic Impact of Credit (A3) have lower eigenvalues, placing them in the fourth and fifth positions.

These results suggest that in the context of an effective credit management strategy, the main emphasis should be placed on technological development and innovation in the credit process, followed by the evaluation of borrowers' financial criteria. While credit security, regulatory compliance, and socio-economic impact are also important, they are not considered as critical as the first two factors. This approach helps in allocating resources and establishing focus on those areas that will have the most significant impact on credit management success.

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