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Optimization Of Loan Classification Criteria For Reducing Credit Risk And Increasing Bank Profitability

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Abstract: Loan classification criteria are fundamental to commercial-bank credit-risk management because they determine when an exposure is treated as performing, requires intensified monitoring, or presents materially elevated risk. Poorly optimized criteria can create two opposite failures: late recognition of deterioration and excessive classification of viable borrowers as risky. The first increases credit losses and provisioning pressure, while the second reduces lending income and can weaken customer relationships. This thesis examines the optimization of loan classification criteria as an economic and analytical decision problem. The proposed approach combines borrower financial indicators, payment behavior, facility characteristics, collateral, sectoral exposure, and macroeconomic conditions with probability-of-default estimates and risk-based thresholds. Particular attention is given to discrimination, calibration, false-negative and false-positive costs, portfolio segmentation, stress testing, and risk-adjusted profitability. The thesis argues that the optimal classification rule should not be selected solely by predictive accuracy. Instead, criteria should minimize the total economic cost of credit risk while preserving profitable lending opportunities and regulatory discipline. A conceptual implementation framework is developed in which model outputs are translated into differentiated monitoring, pricing, provisioning, and collection actions. The approach can help banks identify deterioration earlier, allocate capital more efficiently, improve expected-loss estimation, and increase risk-adjusted returns. The main conclusion is that optimized classification criteria create value when they transform better risk information into timely and consistent managerial decisions.

Keywords: loan classification, credit risk, classification criteria, probability of default, expected credit loss, commercial banks, profitability, risk-based pricing, stress testing, credit scoring.

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1. Introduction

Commercial banks face a structural tension between expanding credit and controlling credit losses. Lending is a principal source of interest and fee income, but it exposes the institution to default, restructuring, delinquency, and recovery risk. Since loan portfolios frequently constitute a major share of bank assets, weaknesses in classification criteria can affect provisions, capital adequacy, earnings stability, liquidity planning, and confidence in the institution.

Loan classification should therefore be treated as a management mechanism rather than a purely administrative procedure. The classification assigned to an exposure determines the intensity of monitoring and can influence pricing, provisioning, collateral requirements, collection procedures, and portfolio limits. The central problem is to identify deterioration early without unnecessarily restricting healthy borrowers.

This thesis focuses on the optimization of classification criteria. Optimization is understood in an economic sense: the preferred criteria are those that generate the best balance between credit-loss prevention and profitable lending. The study is conceptual and methodological and does not claim institution-specific empirical results.

Issues related to reducing credit risk and increasing the profitability of commercial banks are considered one of the important areas of modern banking risk management. Scientific approaches to improving loan classification criteria were initially based on indicators reflecting the borrower's financial condition, statistical classification, and discriminant analysis methods. E. Altman developed a model for determining the probability of corporate bankruptcy using financial indicators and substantiated the possibility of applying financial ratios to the early assessment of credit risk [1]. This study established the initial scientific foundations for quantitatively assessing the financial stability of borrowers and classifying them according to their level of risk.

R. Anderson investigated credit scoring systems from both theoretical and practical perspectives, covering issues related to data collection, processing, statistical modeling, and the automation of credit decisions in retail credit risk management [2]. In his approach, a credit scoring model is considered not merely as a tool for assigning borrowers to risk groups, but as an integrated system closely connected with lending, monitoring, and decision-making processes. This approach demonstrates the need to link loan classification criteria with practical risk management decisions made by banks.

B. Baesens and co-authors conducted a comparative study of the effectiveness of modern classification algorithms in the field of credit scoring and assessed the ability of different models to classify borrowers according to their risk levels [3]. The study focused on the classification accuracy of algorithms and their ability to discriminate between different levels of credit risk. This scientific approach substantiates the importance of comparing several models and selecting the most appropriate one when developing loan classification criteria.

The principles for credit risk management developed by the Basel Committee on Banking Supervision place particular emphasis on systematic mechanisms for identifying, measuring, monitoring, and controlling credit risk [4]. According to these principles, banks should regularly assess the quality of their credit portfolios and identify changes in credit risk in a timely manner. This approach demonstrates the need to improve loan classification criteria not merely as indicators reflecting the current condition of loans, but also as mechanisms capable of identifying risks at an early stage.

Regarding the management of risk data, the principles developed by the Basel Committee emphasize the need for banks to ensure that risk data are complete, accurate, timely, and consistent [5]. The effectiveness of loan classification models directly depends on the quality of the data used and the speed with which such information is delivered to decision-makers. Therefore, data infrastructure and mechanisms for aggregating risk indicators should also be considered important factors in optimizing credit risk.

The guidance developed by the Basel Committee on the recognition of expected credit losses emphasizes a forward-looking approach to credit risk assessment, which takes into account potential future economic conditions [6]. This approach makes it possible to assess potential credit losses in advance rather than identifying deterioration in credit quality only after a default has occurred. Consequently, it demonstrates the need to incorporate not only historical data but also potential future economic conditions when improving loan classification criteria.

L. Breiman proposed the Random Forest algorithm, expanding the possibilities for identifying complex statistical relationships and performing classification based on multiple decision trees [7]. This algorithm can be applied in credit scoring to identify nonlinear relationships among the financial, behavioral, and other characteristics of borrowers. At the same time, when using complex machine-learning models, not only their predictive accuracy but also their stability and interpretability are important considerations.

J. Friedman developed the gradient boosting methodology and demonstrated the possibility of achieving high predictive accuracy by combining sequentially generated predictive models [8]. This approach makes it possible to take into account complex relationships among multiple factors when assessing credit risk. As a result, algorithms such as gradient boosting can provide more detailed segmentation of credit risk compared with traditional statistical models.

D. Hand and W. Henley systematically reviewed statistical classification methods used in

consumer credit scoring and analyzed the advantages and limitations of different statistical techniques [9]. The authors emphasized the importance of appropriate variable selection, data quality, and consideration of classification errors in the credit scoring process. This study demonstrates that optimizing loan classification criteria requires the joint assessment of statistical reliability and economic relevance.

The introduction of the IFRS 9 standard by the International Accounting Standards Board increased the importance of the expected credit loss concept in credit risk assessment [10]. This concept implies that credit risk should be assessed not only on the basis of losses that have already occurred, but also by taking into account potential future losses. From this perspective, loan classification criteria should enable banks to assess expected credit losses more accurately and implement appropriate risk management measures in a timely manner.

S. Lessmann and co-authors investigated the development of machine-learning methods in credit scoring through a comprehensive comparison of modern classification algorithms [11]. The authors assessed the effectiveness of different algorithms in distinguishing borrowers according to their risk levels and demonstrated the need for a comprehensive approach to model selection. These findings substantiate the importance of considering not only the statistical accuracy of a model but also its stability and practical performance under real banking conditions when optimizing loan classification criteria.

R. Merton studied the risk structure of corporate debt and established a theoretical basis for assessing the value of debt instruments through risks associated with a company's assets and financial obligations [12]. This approach makes it possible to assess credit risk in relation to the borrower's financial condition and ability to fulfill its obligations. The Merton model expanded the theoretical possibilities for using market and financial indicators in credit risk assessment.

N. Siddiqi investigated the development and practical implementation of credit risk scorecards, covering the processes of quantitative credit risk assessment, variable selection, scorecard development, and model monitoring [13]. His approach demonstrates the importance of establishing a connection between statistical models and management processes when translating loan classification criteria into practical banking decisions. In particular, the formulation of credit decisions corresponding to different levels of risk is of significant importance for managing the quality of a bank's credit portfolio.

L. Thomas, J. Crook, and D. Edelman examined credit scoring and its application in banking practice, providing extensive coverage of statistical models, scoring systems, and the automation of credit decisions in credit risk assessment [14]. The study demonstrates that credit scoring systems can be applied throughout the lending process, from credit origination to monitoring and portfolio management. This indicates that optimized classification criteria should be applied not only at the stage of loan origination but throughout the entire life cycle of a loan.

T. Hastie, R. Tibshirani, and J. Friedman systematically investigated statistical learning and machine-learning methods, providing theoretical foundations for regression, classification, tree-based models, and ensemble methods [15]. These approaches expand the possibilities for identifying complex data structures and classifying borrowers into different risk groups in credit risk assessment. In particular, when selecting classification algorithms, it is important to evaluate not only the predictive capability of a model but also its generalization ability and stability when applied to new data.

Overall, the reviewed scientific literature demonstrates that the development of loan classification criteria has evolved from traditional financial indicators and statistical methods toward modern approaches such as machine learning, probability of default, expected credit loss, and forward-looking risk assessment. Although existing studies provide substantial coverage of the technical aspects of credit risk identification, the optimization of classification thresholds in conjunction with their economic consequences—particularly credit losses, capital costs, monitoring costs, and banks' risk-adjusted profitability—remains an important area of research. Therefore, this study proposes an approach to optimizing loan classification criteria not solely on the basis of

model accuracy, but also by taking into account misclassification costs, expected credit losses, and risk-adjusted profitability.

2. Methodology

This study employs a conceptual and analytical research approach to optimize loan classification criteria aimed at reducing credit risk and improving the profitability of commercial banks. The research considers borrower financial indicators, payment behavior, loan characteristics, collateral, sectoral exposure, and macroeconomic conditions as key factors influencing the probability of default and loan risk classification. Comparative analysis is applied to evaluate traditional statistical classification methods alongside machine-learning techniques, with model performance assessed in terms of discriminatory power, calibration, stability, and classification accuracy. The study also applies a risk-based approach to determine optimal classification thresholds by incorporating the economic costs of false-negative and false-positive decisions, expected credit losses, and capital requirements. Based on these methodological principles, a conceptual framework is developed that connects loan classification results with credit monitoring, risk-based pricing, provisioning, collection measures, stress testing, and risk-adjusted profitability.[16]

3. Result And Discussion

Loan classification can be based on current status, predicted future deterioration, or a combination of both. Current-status indicators include delinquency, restructuring, covenant breaches, and observed financial weakness. Predictive indicators estimate the probability that an exposure will migrate to a worse risk category over a defined horizon. A forward-looking system combines these dimensions so that the bank can act before a loss becomes unavoidable.

Probability of default (PD) is central to predictive classification. PD estimates the likelihood that a borrower or exposure will default within a specified period, conditional on information available at the prediction date. Loss given default (LGD) reflects the severity of loss if default occurs, while exposure at default (EAD) reflects the amount exposed. Classification criteria should distinguish PD from LGD because strong collateral can reduce loss severity without necessarily reducing the probability of default.[17]

Traditional criteria such as days past due, collateral coverage, and financial ratios remain useful but may be incomplete. A borrower may be deteriorating before missing a payment, while collateral may remain adequate despite weakening repayment capacity. Behavioral and forward-looking information can therefore provide additional lead time.

The Table 1. optimization problem can be represented conceptually as minimizing total expected economic cost: expected credit losses, monitoring and collection costs, capital costs, and the opportunity cost of unnecessarily rejecting or repricing viable loans. Regulatory constraints and minimum risk-management standards remain binding conditions rather than optional objectives.

Table 1. Main components of optimized loan classification

Component	Examples	Purpose
Borrower condition	Leverage, liquidity, profitability, cash flow	Measure repayment capacity
Payment behavior	Days past due, missed/partial payments	Detect emerging stress
Facility structure	Maturity, currency, repayment schedule	Capture exposure-specific risk
Collateral	Loan-to-value, collateral liquidity, guarantees	Assess potential loss severity
External conditions	Interest rates, inflation,	Add forward-looking risk

	unemployment, sector stress	information
Model output	PD, risk score, migration probability	Create comparable risk classes
Thresholds	Risk bands and action triggers	Translate risk estimates into decisions

The analytical approach consists of five stages: defining the classification target; identifying economically meaningful risk variables; comparing candidate statistical or machine-learning models; optimizing classification thresholds according to error costs and expected economic value; and validating the resulting criteria through out-of-time testing and stress scenarios.

The framework emphasizes that model performance must be evaluated on more than one dimension. Discrimination measures whether higher-risk exposures receive higher risk scores. Calibration assesses whether predicted probabilities correspond to observed outcomes. Stability evaluates whether the classification remains useful across time and changing economic conditions.[18]

The most consequential design choice is often the threshold separating one risk class from another. If the threshold is too high, the system will classify too few loans as risky and miss early deterioration. If it is too low, many healthy borrowers will be escalated. These errors are economically asymmetric and should therefore be evaluated using their financial consequences.

A false negative occurs when a genuinely risky exposure is classified as acceptable. The cost can include additional interest not collected, recovery expenses, collateral deterioration, higher provisioning, and capital consumption. A false positive occurs when a relatively healthy exposure is classified as risky. The cost may include unnecessary monitoring, higher provisions, reduced lending, lost interest income, and customer attrition.

Optimal thresholds should therefore be selected by comparing candidate rules using expected loss and risk-adjusted profitability. A threshold that slightly improves statistical recall but severely reduces profitable approvals may not be economically optimal. Conversely, a threshold that preserves loan volume while allowing substantial high-risk exposures to remain untreated is also unacceptable.

Dynamic thresholds may be justified when the macroeconomic environment changes substantially. During a severe downturn, earlier escalation can be economically rational because the cost of delayed intervention increases. However, dynamic rules require governance so that management discretion does not undermine consistency or create opportunities for arbitrary classification.

Table 2. Portfolio segmentation is another optimization mechanism. Corporate, retail, mortgage, agricultural, and small-business portfolios have different risk drivers. Separate criteria may therefore be justified where differences are material and enough historical data exist. Excessive segmentation should be avoided because small samples can create unstable estimates.[19]

Table 2. Illustrative risk-classification thresholds and actions

Risk class	Illustrative PD range*	Typical management response
Low risk	0–2%	Routine monitoring; standard pricing
Moderate risk	>2–5%	Enhanced monitoring; updated borrower information
Elevated risk	>5–10%	Credit review; possible repricing/collateral review

High risk	>10–20%	Intensive monitoring; restructuring/recovery assessment
Severe risk	>20%	Specialized workout and close recovery control

*Illustrative analytical ranges only; actual thresholds must be calibrated to the bank, portfolio, regulatory framework, and observed default experience.

An optimized classification system requires data that reflect information actually available at the time of the decision. Using later information creates look-ahead bias and can make the model appear more accurate than it would be in production. Historical data should therefore be constructed with strict observation dates and information cut-offs.

Figure 1. Candidate models can include logistic regression, decision trees, random forests, gradient boosting, and probability-of-default models. Logistic regression provides a transparent benchmark, while more complex models may capture nonlinear interactions. A challenger model should be adopted only if it provides meaningful incremental value after calibration, stability, interpretability, and economic impact are considered.

Figure 1. Conceptual framework for optimizing loan classification criteria

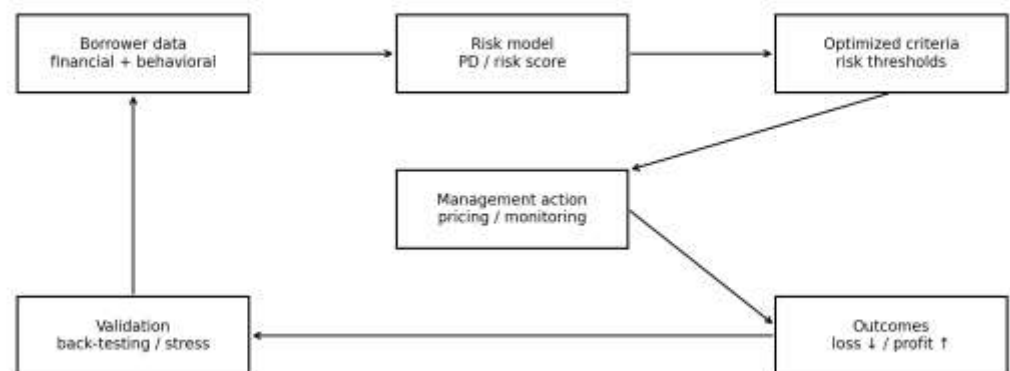


Figure 1. The decision cycle connects risk data, model estimation, optimized thresholds, management action, realized outcomes, and validation.

Optimized criteria reduce credit risk primarily by increasing the lead time between the first observable signs of deterioration and the point at which a loan becomes a severe problem. Earlier warning permits financial review, borrower engagement, restructuring where economically justified, collateral reassessment, and specialized collection.

Better classification also improves portfolio concentration management. When risk classes are analyzed by sector, region, currency, product, and borrower group, management can identify clusters of elevated risk that aggregate portfolio averages may conceal. Limits and underwriting policies can then be adjusted before concentration becomes a major source of loss.

Provisioning quality can also improve. A calibrated forward-looking classification system reduces the likelihood of systematically underestimating or overestimating expected losses. This contributes to more stable financial reporting and more informed capital planning.

The profitability effect comes from risk-adjusted rather than nominal returns. A loan with a high contractual interest rate may be unattractive after expected credit losses, capital charges, and collection costs. Conversely, a lower-rate loan to a low-risk borrower may generate a superior risk-adjusted return. Classification criteria provide the information required to make this distinction.

Risk-based pricing is one direct channel. If estimated risk is reliable, loan terms can be

differentiated according to expected loss and capital use. Better classification also improves allocation of collection resources and reduces unnecessary manual review of low-risk exposures.

The Table 3. main profitability failure mode is overclassification. Excessively conservative criteria can reduce approval rates, increase provisioning, raise customer prices, and push viable borrowers toward competitors. The optimization framework must therefore evaluate the opportunity cost of false positives alongside the loss cost of false negatives.

Table 3. Expected economic effects of optimized criteria

Area	Expected improvement	Potential risk if poorly designed
Credit losses	Earlier intervention and better risk selection	Late recognition of deterioration
Provisioning	Better-calibrated expected losses	Under- or over-provisioning
Pricing	More accurate risk-based pricing	Loss of viable borrowers if pricing is excessive
Capital allocation	Capital directed toward risk-adjusted returns	Inefficient capital consumption
Collections	Priority given to high-value recovery cases	High operating cost or delayed recovery
Portfolio management	Improved concentration visibility	Hidden sector or product concentrations

Validation should use out-of-time samples because credit relationships evolve. Random splits can mix information from different economic periods and may overstate model robustness. Time-based validation, rolling windows, and independent holdout periods provide stronger evidence of real-world performance.

Stress testing should examine adverse combinations of macroeconomic variables, including higher interest rates, currency depreciation, unemployment growth, inflation, and sector contraction. The purpose is not to predict a single future outcome but to identify whether risk classes remain useful when historical relationships are disrupted.

Governance is essential because classification decisions affect customers, provisions, capital, and profitability. Banks should document data sources, variable definitions, model assumptions, thresholds, validation results, limitations, and approved uses. Independent validation should challenge model developers and business owners.

Human overrides may be appropriate when material borrower information is not captured in structured data, but overrides should be controlled through reason codes, authorization levels, and outcome review. Continuous monitoring should track calibration, discrimination, population stability, override rates, and realized default rates. The proposed framework demonstrates that optimization is fundamentally an economic problem. Statistical accuracy is necessary but insufficient. The relevant question is whether the criteria improve the timing and quality of lending, monitoring, provisioning, pricing, and recovery decisions.

There is no universally superior algorithm. Transparent statistical models can be preferable where data are limited and interpretability is critical. Machine-learning models can be valuable when nonlinear interactions materially improve prediction. A hybrid structure in which transparent models serve as benchmarks and advanced models act as challengers provides a practical balance.

The framework also highlights the importance of distinguishing borrower default risk from loss severity. Collateral should reduce the estimated loss given default where appropriate, but it should not automatically conceal deterioration in the borrower's repayment capacity.

For banks with limited historical default data, the priority should be data quality, conservative assumptions, local validation, and strong monitoring rather than immediate deployment of highly complex algorithms. Model sophistication cannot compensate for weak data or poorly defined targets.[20]

4. Conclusion

Optimization of loan classification criteria can reduce credit risk and increase sustainable bank profitability when risk information is translated into timely management actions. The strongest framework combines borrower financial condition, payment behavior, facility characteristics, collateral, sector exposure, and macroeconomic information with calibrated probability-of-default estimates.

Classification thresholds should be selected according to the asymmetric economic costs of false negatives and false positives. They should be tested through back-testing, out-of-time validation, stress testing, and risk-adjusted profitability analysis. Each risk class should trigger a clearly defined response in monitoring, pricing, provisioning, or recovery.

The principal conclusion is that the best classification system is not necessarily the most complex or the most statistically accurate. It is the system that consistently identifies meaningful deterioration early, limits avoidable losses, allocates capital efficiently, preserves profitable lending opportunities, and remains stable and governable as the economic environment changes.

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