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Credit Risk Analysis

Paraphrased Research Title

Examining How Banks Assess and Manage Credit Risk

Introduction

In today's fast-changing financial landscape, perhaps the biggest challenge for banks and other financial services firms is managing the risk associated with lending money. Lending always involves uncertainty, as financial services firms do not know whether borrowing customers will be able to repay their obligations. Uncertainty is the nature of credit risk: credit risk refers to the risk that a customer will be unable to meet its financial commitments to the lender in accordance with the deemed credit terms and that the lender incurs a financial loss. Credit risk must be managed effectively not only for the financial health of individual firms but also for the stability of the global economy as a whole. Banks are conduits facilitating intermediaries of credit from depositors' savings to borrowers. These institutions are essential to the efficient and responsible allocation of credit; however, the global marketplace has complicated risk assessment. Moreover, loans and financial products are complicated, as are the credit risks posed by borrowers. Determining risk accurately offers value to the lending institution insofar as it allows them to develop a trend of borrower behavior and acknowledge the probability bond of default, as well as obtain recourse measures such as interest rate, collateral, or application denial. Poor assessment of credit can lead to loan defaults, which equate to financial losses or collapse of a financial institution (Ahmed *et al*, 2021). No financial collapse was more visible and severe than during the global financial collapse of 2008. The goal of this research paper is to examine how banks evaluate, assess, and mitigate credit risk, contrasting the old and traditional credit risk assessment methods

with new methods based on data. It will identify the theoretical implications of risk management, analyze previous empirical studies, and assess the practical techniques used by banks to minimize financial losses from bad debts. By discussing the difficulty banks face in alleviating credit risk as well as possible means to do so, this research contributes knowledge to the literature on bank financial stability and safety.

Problem Statement

Despite the dramatic enhancements in financial technology and risk management, financial institutions and banking still struggle with credit risk analysis. The reason is that lending is an intricate decision of operation where an organization evaluates the likelihood of a borrower fulfilling his or her vow to repay a loan. Despite the desire to make a factual and informed decision on the credit risk using all accessible data, the fact is that there could be unforeseeable variations in the circumstances of the borrower and happenings in the business of the lender or other factors affecting the overall economy. When borrowers default on their financial obligations, this is of great implication to the financial institution and the economy at large, particularly when it involves a number of borrowers. It becomes quite hard to access correct and credible and consequently more up-to-date data concerning borrowers, which is one of the significant problems when it comes to guaranteeing credit risk. Misinformation or the unavailability of full information would result in either the granting of risky loans or the rejection of potentially good borrowers. Besides that, the capacity of the financial market to operate on the basis of such indications of increasing inflation or workforce and international financial events in quick acquiring would have the potential to influence the borrower's capacity to remunerate on a loan in quick beating (Sharma et al., 2024). The challenges instead are usually on the forecasting of these and effective integration into their risk assessment model.

The other weakness is the limitations that are involved with conventional credit assessment processes. Most institutions continue to make lending judgments based on the conventional method of simple financial ratios, credit scores, and expert judgments as a result of opinion. Although these processes offer some helpful information, they might not be sufficient to reflect the complexity of defining behaviors of borrowers or the macro environment of economic conditions. Banks may either underestimate or overestimate the risk of credit, hence making bad lending decisions. Thus, there are still certain fears about the influx of advanced statistical models and machine-learning practices. They rely, however, on the historical data whose images on the part of borrowers, particularly reinforced by economic turbulence, might be recalcitrant to forward extrapolations. The example of overly near-blind trust towards the automated systems can also be inclined towards laxity in the views of the qualitative factors, the character of the borrower or the unexpected disruption of the market.

There is also the challenge posed by regulations as an aspect of the industry. In the efforts to innovate in their assessment strategy, banks and other credit providers are forced to find a solution to meet the requirements of the new regulations, such as Basel III that demand both quantitative and qualitative measures. There is even greater difficulty with the use of high-level machine learning models, which are acting as black boxes. The models do not allow the needful rationales to be put forth to the risk managers and regulatory authorities in credit and lending decisions. The appropriate models with the appropriate predictive ability of risks and ensuring that the models remain sufficiently transparent to satisfy both the predatory lending and other regulation needs of the industry is this dilemma.

Research Objectives

This study aims to:

1. Define credit risk and explain its merits in the banking sector.
2. Identify and describe the main methods banks use to assess and manage credit risk, including both traditional and modern techniques.
3. Examine the challenges banks face when trying to predict and control credit risk.
4. Suggest practical recommendations to improve the accuracy and effectiveness of credit risk analysis in financial institutions.

Significance of the Study

The importance of this research is based on the fact that credit risk analysis is important to a bank when looking at the stability of the entire economy. During the lending process, the bankers are exposed to the risk of default by the borrowers. The improper management of such risks can cause enormous financial losses, a high rate of bad loans, and bank defaults, and in turn, this is transmitted to the whole financial system. Since banks evaluate and deal with credit risk, this research provides recommendations on how the issue can be further enhanced to reduce financial losses. It shows that the old approach methodologies failed, whereas the new data-driven approaches like statistical models and machine learning could help to address such risks.

With this, the accuracy of predictions concerning credit risk will improve within the exact constraints of the parameters defined for decision-making. Additionally, this approach will assist borrowers by promoting fair and transparent lending practices. Such an assessment will improve deserving borrowers' access to loans and make sure that the banks restrict lending to the riskier ones. Thus, it will establish a stable and well-functioning environment for both lenders and borrowers.

Research Questions

1. What is credit risk, and why is it important for banks to manage it effectively?
2. What are the traditional and modern methods used by banks to assess credit risk?
3. What challenges do banks encounter in managing credit risk?

Research Hypotheses

In accordance with the research objectives and questions, the hypotheses of this study are as follows:

Main Hypothesis (H0): The adoption of modern data-based credit risk assessment techniques and the effectiveness of credit risk management of banking institutions are statistically significant.

Sub-Hypotheses:

H1: Conventional credit risk evaluation tools are quite deficient in the ability to predict borrower default in modern economic contexts.

H2: The modern statistical models and machine learning outperform traditional models in predicting credit risk.

H3: Banks that adopt a hybrid model of using both data-driven analytics and traditional expert judgment have better credit risk management results as compared to banks that adopt either of the models.

H4: The quality of data, regulatory compliance, and transparency of models have a strong moderating role in the efficacy of contemporary credit risk assessment methods.

Theoretical Framework

This paper is based on the theory of risk management because it is the main theoretical perspective of current research, which is the identification, measurement, and management of financial risks with the purpose of securing assets and revenues for an organization. Jorion (2007) notes that proper risk management assumes that one understands the nature of the risks in question,

how to estimate them, and how to develop appropriate responses towards them with the purpose of alleviating them. In credit risk, the analysis is a computation of the likelihood of default of a borrower and what risk is possible to be assumed by a bank safely. Another critical theoretical foundation is the Basel Accords, which are a set of international banking regulations created by the Basel Committee on Banking Supervision. Basel II and Basel III included critical provisions for credit risk management with the requirements that banks set aside a minimum capital base to cover their possible loss due to default on loans (Alhassan and Abiola, 2014). Such agreements also focused on the significance of quantitative models as well as qualitative estimates in measuring credit risk.

Literature Review

The chapter discusses already available knowledge on credit risk evaluation and management in banking systems. The chapter is compartmentalized in order to understand the theory and practice of credit risk analysis mechanisms. The analysis moves from the old-school techniques to the new-age approaches in the evaluation of risk. The chapter discusses the dependent variable, which is the effectiveness of managing credit risk and the independent variable, which is the method of assessment that the banks use. This literature review is aimed at detecting the complexities in existing literature and through the review, the chapter intends to provide a contribution to knowledge of credit risk management practices.

The overview of the research conducted by numerous researchers and financial experts over the years on how banks and financial institutions evaluate and manage credit risk has significantly influenced these institutions. Historically, the qualitative assessment of credit risk was based more on expert inference, borrower interviews, and reviews of financial statements. Altman (1968) postulated one of the oldest models in credit risk analysis, which was the Z-score

model for predicting business bankruptcy by means of financial ratios. Although it was innovative at the time, this method faced several complications due to its clearly restrictive reliance on past-oriented financial data and its failure to consider future economic changes. As markets grew more complicated, banks turned to quantitative models to further improve assessments of credit risk. Credit scoring models are widely accepted for evaluating the general creditworthiness of borrowers. Interest is expressed to appreciate how well the lender assesses the ability of borrowers to repay the loan. Among the factors considered are payment limits and credit usage, which help present scores to the lender. According to Golbayani, Florescu & Chatterjee (2020) scoring improves the efficiency of decisions decided by credit in respect of loans and reduces the risks of human errors.

In recent years, technological advances have led to models that are more sophisticated in credit risk analysis. Machine learning and artificial intelligence have drawn the most attention for their ability to process large volumes of data and find rather complex patterns. These authors support their claims by comparing their models to other approaches, such as decision trees, neural networks, and support vector machines, which have demonstrated superiority over traditional statistical models in predicting defaults, as indicated by Baesens et al. (2003). The advanced systems pose a number of challenges: these include overfitting, data privacy issues, and the need for more specialized expertise.

Dependent Variable: Credit Risk Management Effectiveness

This study evaluates the efficiency of credit risk management in the banking industry that measures the efficiency of the credit risk management in predicting, measuring, and mitigating possible losses caused by default of borrowers on loans. This variable is further subdivided into measurement indices such as the prediction of defaults, which is predicated on the proper

identification and prediction of the risk level of the borrowers; the measurement of financial loss prevention by better ratios of non-performing loans; and the overall risk of the bank loan stock based on the capital and provision balances. Besides, credit risk management effectiveness also encompasses an adequate return on investments as a result of risk management and general direction of credit decisions. The flexibility of the bank in terms of regulating the economy and changing the risk parameters to adapt to the new trends of borrowers is also a part of this variable. This variable evaluation constitutes quantitative and qualitative aspects such as default rates, loss given default, exposure at default, and the completeness and effectiveness of the risk management systems.

Independent Variable: Data-Driven Assessment Techniques

The independent one includes the practices for assessing credit risk in banks, specifically the application and utilization of data science tools. These are older techniques, like credit scoring, financial statement analysis, and collateral-advocated lending, and more recent techniques, including statistical models, machine learning, and artificial intelligence. Techniques range from basic credit scoring systems to the use of advanced neural and ensemble methods for the analysis of large structured and unstructured data sets. Factors affecting the implementation of this variable include the respect for the quality and completeness of data banks possessed, the level of the technological infrastructure supporting advanced analytics, the skillset of credit analysts and data scientists, and the use of 'smart' automation as a complement to human control. The independent variable also involves the degree of movement from qualitative to quantitative risk assessment in models that banks employ, the frequency of model updating and validation, and the use of real-time data in credit decisions.

Summary and Discussion of Literature Review

The shift from Altman's innovative Z-score model to available machine learning systems is part of a broader move in finance toward data-rich and algorithmic decision-making. However, it has not been all positive. The past demonstrated significant shortcomings of quantitative risk models, particularly with respect to tail risk, in 2008. In addition, all of these tools are systematically flawed when the underlying assumptions about representative market conditions are no longer valid. This is an important lesson from history—regardless of any amount of advanced technique and sophistication, one must have human supervision and discretion. The research gaps this study addresses is in real-life integration: while there is much research that compares the technical efficacy of advanced models, there is less research on organizational or regulatory or operational frameworks to leverage the extensive real-life utility of the theoretical benefits of sophisticated risk models. One must employ contextual and framing conditions to move theoretical benefits of advanced life integration to improved risk management practice.

Theoretical Framework of the Study

The current research is based on three related theoretical models that unanimously describe the management of credit risk in banking institutions. To begin with, the risk management theory offers the theoretical aspect, which considers the systematic process of identifying, measuring, and alleviating financial uncertainties. As Jorion (2007) points out, to effectively manage risks, one has to understand the nature of risks, measure the level of impact of risks, and put in place relevant control mechanisms. This theory is applied within the credit risk of a specific context in that banks use the theory to calculate the default probabilities and to estimate the acceptable level of risk exposure so as to protect the institutional assets and to sustain profitability.

In addition, the Basel Accords framework provides the theoretical basis of the regulations, which sets the international standards of the credit risk management practices. Basel II and Basel

III proposed extensive provisions under which banks are required to hold minimum capital requirements in relation to their risk exposure that focused on quantitative modelling, as well as qualitative judgement, in credit rating (Alhassan and Abiola, 2014). These agreements put the risk management theory into practice by laying down capital adequacy requirements, common risk measurement methods, and review processes by the supervisory bodies to maintain the stability of the banking systems.

Finally, the Information Asymmetry Theory explains the basic problem with credit relations when lenders have incomplete data on the actual creditworthiness and intentions of borrowers. According to this theoretical lens, it is possible to explain why more traditional assessment approaches based on observable financial data might be inadequate and why more sophisticated analytical approaches that manipulate more data and reveal obscured patterns may benefit the theoretical benefits of reducing information asymmetry between lenders and borrowers and enhancing the accuracy of credit decisions and lessening adverse selection issues in lending markets.

Theoretical Premises

This study operates under several theoretical assumptions that shape its analysis of credit risk management in banking. First, the study assumes the importance of having accurate and complete financial data for reliable credit risk analysis. If the bank's information is incomplete or outdated, it may make unnecessary and poor lending decisions that may lead to elevated defaults. Secondly, the study recognizes that no one model for determining credit risk can ever be perfect. Even if a bank employed sophisticated statistical models through machine learning, these algorithms will not be without error. Hence, credit risk management often charges for the quantity of analysis but always requires the ultimate judgment of experienced financial analysts.

Thirdly, the idea assumes economic and market-related factors are important to credit risk, as fluctuations in inflation, employment, or global market stability may have long- or short-term effects on loan payments through modifications to borrower solvency, etc. As external factors can affect borrower payment ability, these are inputs to off-the-shelf risk models. Finally, the idea assumes better tools for assessing credit risk help support financial resiliency as banks help to manage loss mitigation and better meet the needs of customers.

Research Methodology

This chapter presents the methodological framework employed in the research study, which provides an overview of the systematic approach used to examine credit risk assessment and management practices in banks. The methodology covers the research design, the characteristics of the population and sample, data collection methods, the scope and limitations of the study, and the methods of analysis. This chapter clarifies how the study was carried out and supports the basis for assessing the validity and reliability of the conclusions reached in the following chapters.

In the study of credit risk assessment and management practice in the banks, researchers apply the descriptive and comparative approach. The study is mostly a document-based one; it entails an analysis of scholarly literature, financial literature, regulatory literature, and published case studies. This is a document-based research approach that can allow the researcher to explore the management of credit risk by banks and does not need to collect primary data. The descriptive nature of the study explains what credit risk is and outlines the various practices that banks use to measure and control it. In the process of doing the document-based qualitative analysis, the researcher discovered both offline approaches, such as credit scoring systems, financial ratios, and the professional judgment of the management, and newer approaches, such as statistical modeling and machine learning technology. The comparative aspect of the study examines the weaknesses

and strengths of these two approaches to credit risk assessment. The research will compare the traditional approaches with those of different technology sources to establish the extent to which the approaches are effective in forecasting how borrowers will default on their loans and cause primary financial losses.

Information sources of the qualitative research applied in this report consisted of: This study evaluated scholarly research reports from finance and banking journals. Now that you have been reported by financial regulation authorities, such as those published by the Basel Committee on Banking Supervision. Bank credit risk techniques Case studies of techniques using advanced credit risk assessment techniques. Books and Internet resources that explore the risk management theory and credit risk models are available. The qualitative study did not involve primary data, such as surveys or interviews, to measure the results because of time and resource limitations and the choice to conduct the study using the analysis of secondary data only. This approach will ensure an objective and comprehensive understanding of how the banking sector measures and manages credit risk at this stage, as well as improvements in credit risk management and evaluation.

Research Design

The study employs a comparative approach to a descriptive-analytical research design as a way of examining the practices of credit risk assessment. It is non-experimental and cross-sectional and explores the current practices and reported findings instead of applying an experimental or interventional approach. The research is qualitative in that it will be possible to have a holistic overview of the traditional and modern ways of practicing credit risk, in addition to undertaking a systematic comparison of their effectiveness, efficacy, strengths, and weaknesses in various banking situations.

Research Community

The population under research comprises commercial banking institutions operating in the developed and emerging markets in both retail and corporate lending. The target population will be large multinational banks, regional commercial banks, and specialty lending organizations that have credit risk management and publicly recorded data on loan performance. The geographic target primarily covers North America, European institutions, and select roofing Asian markets subject to the banking regulation of disclosure of the risk management practices.

Sample Characteristics

The sample of the study includes documented case studies, published research evidence, and regulatory papers of around 15-20 large banking companies that can be found operating in a wide variety of circumstances. The main selection criteria include those banks that have recorded credit risk measures in the past five years, those that have used both old and new evaluation methods, and those that operate under Basel II or Basel III regulations. The sample is also purposely a combination of big, medium, and small banks so that a variety of risk management practices and possible resource capabilities are present.

Sample Size Determination

Since it is a documentary research design, the sample size will be based on the availability and quality of published literature instead of performing a power calculation based on a statistical analysis. It incorporates all pertinent peer-reviewed scholarly papers (2015-2024), the regulatory reports of the key banking supervision authorities, and published case studies of the implementation institutions. Thoroughness of modern practices is also guaranteed by this study, and a selection of high-quality and methodologically sound information is made.

Data Collection Procedures

The information is gathered in a multi-source, systematic fashion by beginning with the search of academic databases with the use of keywords such as "credit risk," "banking habits," and "evaluation of risk methods." Peer-reviewed journals in the banking and finance fields with a heavy emphasis on empirical research launched from 2015 to 2024 will be the leading data sources since they would allow seeing recent banking practices. The secondary sources of data include regulations by the Basel Committee on Banking Supervision, documents of the central bank, reports of financial stability and white papers of big consulting companies. Data collection will involve screening of abstracts to determine relevancy of abstracts, retrieval of full-text documents, extraction of key findings in a structured database, and categorization of findings by risk assessment methodology, risk performance outcome, and risk institutional characteristics.

Study Scope and Limitations

The paper is dedicated to the data concerning credit risk estimation and management without mentioning other banking risks, including operational, market, or liquidity risk. Speaking of time frame, the paper is focused on the path from the traditional methods that were developed in the 1960s-1980s to the modern machine learning methods that were invented in the 2010s-2020s. The research does not go as far as to resort to primary data collection in terms of survey and interviewing resources and access to proprietary banking data. Finally, the results might not be applicable to the context of small community banks, microfinance institutions, or non-bank lenders, which exist in a very different regulatory environment and technological environment.

Statistical Analysis Method.

The qualitative comparative methods of analysis are used instead of statistical hypothesis testing because the data resources are primarily documentary in nature. The analysis model utilizes thematic analysis to determine trends within the literature sources, comparative analysis to

determine the strengths and weaknesses of the methods in comparison and synthesis of results to make findings on the best practices.

Practical Study

Data Analysis

Even though this study is essentially a literature-based study and does not require the collection of primary data or statistical analysis of raw banking data, this part summarizes practical implications and empirical results that have already been reported in the published literature. It is not a comprehensive overview of all the body of empirical literature that has taken into account the effectiveness of credit risk models, but the evidence presented by a number of empirical literature suggests that there are similar trends in the efficacy of different types of credit risk modeling and approaches. As an example, in their study, Baesens et al. (2003) discovered that machine learning models represented classification accuracy rates of 75 to 82 percent compared to traditional logistic regression models with classification accuracy rates of 68–73 percent. Even more recently, there has been additional evidence of improvement, with various ensemble methods and deep learning approaches displaying accuracy rates higher than 85% in some contexts.

Findings & Analysis

This section highlights the major findings of the study, focusing on how banks analyze and monitor credit risk utilizing traditional methods and more modern approaches or combinations of technologies. Furthermore, limited comparisons will be made based on the strengths and weaknesses of both approaches as well as how effective they are in practice in this sector. Published case studies from implementing agencies have indicated that the method of assessment has a large influence on key performance indicators. Institutions that are using advanced analytics indicate that their default rates are 15–25% lower than traditional methods, based on baseline performance. Loss given default measures improved by 10-18% when sophisticated models improved the

predictive power to price risk and collateral needs more accurately. Successful implementations in the literature tend to share similar characteristics, such as strong management support for data-informed decision-making, multi-phased organizational implementation of analytics to promote organizational learning, retaining expert judgment to act as a validation layer to model output and continuous monitoring of model performance with updates based upon newly discovered patterns.

Traditional Credit Risk Assessment Methods

Banks have depended on traditional credit risk assessment techniques for many years. Traditional assessment techniques include credit scoring techniques, financial statement analysis, and judgment-based assessment.

Credit scoring techniques, especially FICO scores, are prevalent in consumer lending through banks. Credit scoring techniques assign a number to borrowers based on their allegiance and ownership, external obligations, payment behavior as reported to the creditor and other parameters. Higher FICO scores almost always present less credit risk. Muigai & Maina (2018) references that credit scoring techniques are efficient, objective, and scalable when applied to retail banking.

Corporate lending commonly applies financial statement analysis. Banks are engaged in the assessment of the company's liquidity, profitability, and solvency from quantitative measures that use ratios such as current ratio, debt-to-equity ratio, and interest coverage ratio. Altman's Z-score model, which predicted business bankruptcies through the amalgamation of various ratios, could be one of the first applications of this method.

Limitations of Traditional Methods

Although these methods historically have been successfully applied in the banking sector for over 40 years, they have the following shortcomings: The demand for using a linear

combination of historical data is limited in its effectiveness as an indicator of potential future risk. The capacity to handle extensive and intricate data sets is limited. Judgment-based assessments are generally subject to human error or may be highly inappropriate given bias due to judgment. Responses to changing market conditions continue to be slow.

Modern Credit Risk Assessment Methods

Technology advancements have significantly reshaped credit risk assessment through statistical modeling and machine learning. Statistical models can be used to assess the probability of loan defaults using various financial and demographic data and, correspondingly, variables. Examples of these statistical models are logistic regression and discriminant analysis. Bhatore, Mohan & Reddy (2020) noted that machine learning (ML) modeling is the dominant approach for identifying complexity, considering nonlinear relationships, and interpreting parcel-level data into monetarily distinct groups of potential loans for labeling. The most commonly used ML techniques include:

1. Decision Trees—a modeling method using information from numerous financial questions to categorize potential borrowing opportunities by risk types.
2. Random Forests—an ensemble approach used by decision trees in a method that predicts by classifying sites by decision tree forests.

Baesens et al. (2003) reported that default predictions using machine learning models generally outperform more traditional models; the sheer volume of data that machine learning models can process and their ability to learn from new patterns over time are superior to traditional methods.

Strengths of Modern Methods

Contemporary methods have the ability to process large, heterogeneous, and real-time data sets with ease.

Adapts to changes in borrower behavior and market changes quickly.

Eliminate bias associated with human decision-making.

Increase prediction accuracy, and therefore, decrease financial loss.

Limitations of Modern Methods

These methods depend on well-formed, high-quality data.

Interpretation and transparency can be complicated (black-box models such as ANNs).

Require extensive technology and people investment.

Privacy or ethical concerns related to data.

Comparative Analysis

A comparison of the traditional credit risk approaches and modern credit risk methods highlights the explicit tradeoffs between two different approaches. Conventional credit risk approaches have the following benefits: they are relatively easy to interpret and are straightforward to implement, and they use proven financial metrics and professional judgement; but they fail to cope with high-volume and complex data, as well as being incapable of responding to the changes in a fast-changing economy. Although modern methods allow greater predictive validity and scalability, modern methods can be difficult to interpret, and only a small amount of technical knowledge is required to create, apply, and maintain them. In particular, there is significant predictive scope when utilizing machine learning models to identify patterns in large and complex data patterns, and due to their speed and capacity to evaluate higher volumes or more

complex patterns, they can identify complex relationships and variables that may not have previously been developed in traditional credit approaches.

In identifying an overarching strategy, recent patterns emerging from industry best practices suggest that organizations are adopting hybrid models as their primary mode of evaluation. An example of this implementation is for organizations such as banks to incorporate a combination of statistical models and AI or machine learning methods to do their primary assessment and then incorporate expert judgment on the final verification of loan amount, including considering factors related to the applicant that could introduce additional information not accounted for by the initial assessment, such as borrower recommendations or how the applicant fits into the organization's other loans.

Challenges in Credit Risk Management

While these advanced tools are available to banks, they continue to face a number of challenges around how they approach and manage credit risk:

Data Quality: Any incomplete or inaccurate data will weaken their model quality.

Compliance to regulation: Banks must certify that their modeling practices track against financial regulations such as the Basel Accords.

Model Risk: While automation can serve as a benefit to banks' modern credit risk measurement, banks must reckon with the risk of over-reliance if their credit risk assessment model is poorly designed or if the modeling assumptions become obsolete in the future (Bi & Bao, 2024).

Discussion

This study shows that credit risk management in the banking industry has come far but has also advanced from using more static methods, such as credit scoring or financial ratios, to more advanced predictive methods, such as machine learning and statistical models. While these more

dynamic predictive methods have provided more accuracy and effectiveness in preventing loan defaults, there are challenges. Data quality, transparency of the model, and ethics of automated decision-making in credit risk management entailed in using predictive analytics and machine learning will provide challenges to banks. The results of the research indicate that using traditional or modern approaches to credit risk management is not sufficient. Another better approach is to implement a hybrid approach to credit risk management, which entails a commitment to either data-driven predictive analytics and its related tools or increased reliance on the judgment of credit practitioners. There will also be the need to remain on the current state of modeling with credit risk by observing the continuous risk development and adherence to the regulatory obligations or requirements to keep the credit risk management within reach.

Research Recommendations

I suggest that banks adopt a hybrid method to credit risk that incorporates the advantages of traditional expert judgement with the machine learning features of modern, predictive analytics. Financial institutions need to continue to focus on advancing organization-level data quality and infrastructure to provide advanced analytical modeling at an organizational level, which also sets up regular and ongoing staff operational training based on traditional risk analysis with a mix of emerging tools and technology. Banks must also routinely monitor and re-evaluate risk models to ensure that risk assessments and decision-making at the bank related to credit risk are actualized in the freshest economic context and regulatory landscape. Finally, banks should also be introducing ethical lending methods while facilitating fairness in lending with full transparency where relevant, with respect to credit background decisions, while protecting the borrower's personally identifiable information (PII) in accordance with privacy legislation.

Limitations

While this study provides useful information on assessing and managing credit risk, there are several limitations that need to be addressed. Firstly, the study purely relies on the use of secondary data from existing literature, financial reports, and case studies (Sironi *et al*, 2004). The authors did not collect any primary data by surveying or interviewing participants involved in credit risk management, which may result in a limitation regarding the richness and timeliness of the findings. Secondly, although the study provides an overall outline of risk assessment and management in the banking sector, it may not apply directly, or at all, to insurers or fintech lenders. Finally, because technology is rapidly advancing, some advanced techniques for assessing risk will always be evolving to the point of becoming outdated during the research stage itself.

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English Abstract

The study investigates credit risk assessment and management practices in commercial banks, focusing on traditional and modern data driven approaches. By reviewing literature and systematically examining documented banking practices, the study explores how banks could improve the effectiveness of credit risk management. The results suggest that both machine learning and statistical models can offer greater predictive accuracy than traditional methods; however, effective application and use of these new technologies mean embedding these methods with expert judgment, ensuring that appropriate data infrastructure is developed and implemented, and providing for continuous validation of the model. Hybrid approaches are suggested to leverage the strengths of traditional and new model types, while allowing for the consideration of new data quality, regulatory compliance, and model transparency challenges. This study addresses both theoretical understanding and practical implementation of credit risk management in contemporary banking contexts.