Jurnal ELTIKOM :
Jurnal Teknik Elektro, Teknologi Informasi dan Komputer

Vol. 8, No. 2, December 2024, page. 100-110
ISSN 2598-3245 (Print), ISSN 2598-3288 (Online)
DOI: http://doi.org/10.31961/eltikom.v8i2.1156
Available online at http://eltikom.poliban.ac.id

SYSTEMATIC LITERATURE REVIEW: IDENTIFYING KEY VARIABLES AND MEASURING MAXIMUM LOAN LIMITS

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Received: 20 May 2024 – Revised: 12 September 2024 – Accepted: 23 September 2024

ABSTRACT

This systematic literature review aims to identify key variables and measurement methods for determining maximum credit loan limits, following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The complexity of setting an optimal credit limit to manage credit risk effectively presents a significant challenge. Establishing an efficient maximum loan limit is essential to mitigate credit risk, as an overly high limit increases default potential, while an excessively low limit restricts the financial institution's growth. This study identifies key variables and measurement methods, including Machine Learning techniques, Neural Networks, and traditional statistical approaches. Machine Learning models, such as Random Forest and Gradient Boosting, often surpass traditional methods in handling large, unstructured datasets due to their capacity for modeling complex, non-linear relationships. Conversely, traditional methods like logistic regression may be more suitable for smaller datasets, offering better interpretability and ease of use. The results indicate that systematic variable identification and the use of appropriate measurement methods can enable financial institutions to manage credit loan risk more effectively, supporting the development of sound credit policies.

***Keywords**:credit loan, loan limit, PRISMA, SLR.*

I. INTRODUCTION

CREDIT risk is a major concern in banking and financial activities, significantly impacting the stability of financial institutions and the broader economy [1]. In simple terms, credit risk refers to the possibility that a borrower may fail to fulfill their obligations under the agreed terms and conditions [2]. Poor credit risk management can lead to not only direct accounting losses but also opportunity costs, transaction costs, and expenses related to non-performing assets, all of which can affect a bank's portfolio health and liquidity risk [3].

According to Sara Halou's research, credit risk remains the most significant and dangerous risk for banks. Managing and evaluating credit risk is essential for continuously improving bank performance in the financial market. A bank's involvement in providing substantial credit loans and a debtor's inability to repay them can threaten the bank's financial stability and potentially trigger a broader financial crisis [4]. Thus, understanding credit loan risk, particularly in setting credit loan limits, is crucial. Ileberi Emmanuel's research notes that poorly managed credit risk can lead to substantial financial losses for financial institutions. Loan payment defaults can decrease profitability, cause capital losses, and even lead to potential bankruptcy [5]. Gryzunova, N. V.'s research suggests that setting an appropriate credit limit requires assessing the credit risk associated with the customer's repayment capacity. Therefore, determining credit loan limits not only enhances company competitiveness but also plays a vital role in effectively managing credit risk [6].

This study seeks to identify key variables and measurement methods that effectively determine maximum loan limits. Efficient lending limits are crucial for reducing credit risk, as excessively high limits increase the risk of default, while overly low limits restrict financial institution growth. Thus, understanding credit risk, especially in determining credit loan limits, is essential.

TABLE 1
RESEARCH QUESTIONS AND OBJECTIVES

Question	Destination
What are the key attributes or variables used to determine the maximum loan limit?	Identify key attributes or variables in determining the maximum credit loan limit.
What are the commonly used methods of measuring credit limit?	Analyze the commonly used methods of measuring credit loan limits.
What are some of the key issues or limitations in determining a credit borrowing limit?	Identify key issues or limitations encountered in determining the credit loan limit.

TABLE 2
APPLICATION OF INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	Conference article and Journal article
Exclusion Criteria	Duplicated article, unrelated article, review article, no access to full documents, and unranked article.

Figure 1. Literature Review Methodology

This study aims to offer practical recommendations for financial institutions. For example, by integrating Machine Learning models with real-time credit monitoring systems, banks can adjust credit limits dynamically based on evolving customer risk profiles. Additionally, stress testing under various economic scenarios can help institutions prepare for potential financial crises, exploring interactions and interdependencies among key variables. For instance, customer income and credit history often display a nonlinear relationship with credit risk; while higher income usually correlates with lower risk, a poor credit history can offset this effect. The dynamics between loan size and repayment period also significantly influence risk assessment, warranting further investigation [7].

The novelty of this study lies in applying PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to conduct a systematic literature review. Beyond academic findings, it is essential to incorporate insights from real-world case studies. For example, financial institutions like Bank X have successfully employed Machine Learning algorithms to manage loan approvals, achieving a 15% reduction in default rates over the past two years. Similarly, by utilizing structured decision trees to assess customer income and credit history, Company Y has shortened loan processing time by 30% [8]. Integrating real-world data enhances the practical relevance of the findings, illustrating how these theoretical insights can lead to measurable business improvements. The results offer insights for developing more efficient credit policies, aiding financial institutions in managing credit lending risks more effectively.

This study adopts a transparent and systematic approach, aiming to increase scientific rigor and contribute to reliable knowledge development. Consequently, it is expected to benefit not only academics in banking and finance but also practitioners and policymakers involved in credit loan risk management.

II. RESEARCH METHOD

The research methodology follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Using this approach in credit risk research provides the benefits of a structured framework, enhanced research quality, reproducibility, and ease of comparison across studies [9]. Figure 1 presents a diagram outlining the main steps in this research process.

A. Determination of Research Questions and Objectives

To ensure a structured approach in the literature search and analysis, the first step involves formulating research questions and objectives aligned with the study topic. Table 1 shows the research questions and objectives.

B. Literature Search and Selection Strategy

Relevant keywords related to the research topic were selected to construct search terms, which were then applied to Watase UAKE, an online system designed to facilitate research collaboration between researchers. These keywords helped identify papers pertinent to the study topic.

This study considered articles from journals and conferences published between 2019 and May 2024. As shown in Table 2, inclusion and exclusion criteria were established for selecting and excluding articles.

C. Data Extraction

The data extraction process in the study on credit risk involves gathering relevant information from articles selected for analysis. First, the study identifies key attributes or variables used to determine loan limits, such as customer risk profile, market conditions, internal bank policies, and applicable regulations. Second, it evaluates common methods for measuring loan limits by analyzing various loan risk assessment techniques used by financial institutions. Third, it identifies key challenges in determining loan limits, including economic fluctuations and regulatory changes. Through a comprehensive data extraction process, this study aims to provide an in-depth understanding of key variables, measurement methods, and challenges in setting credit loan limits, thus contributing to both academic and practical knowledge on credit risk in banking and finance.

D. Analyzing Data and Synthesizing Findings

Data analysis began with processing and organizing the extracted data into tables for effective examination. An in-depth analysis was conducted to identify significant patterns or trends, such as the relationships between risk measurement methods and bank financial performance, as well as the influence

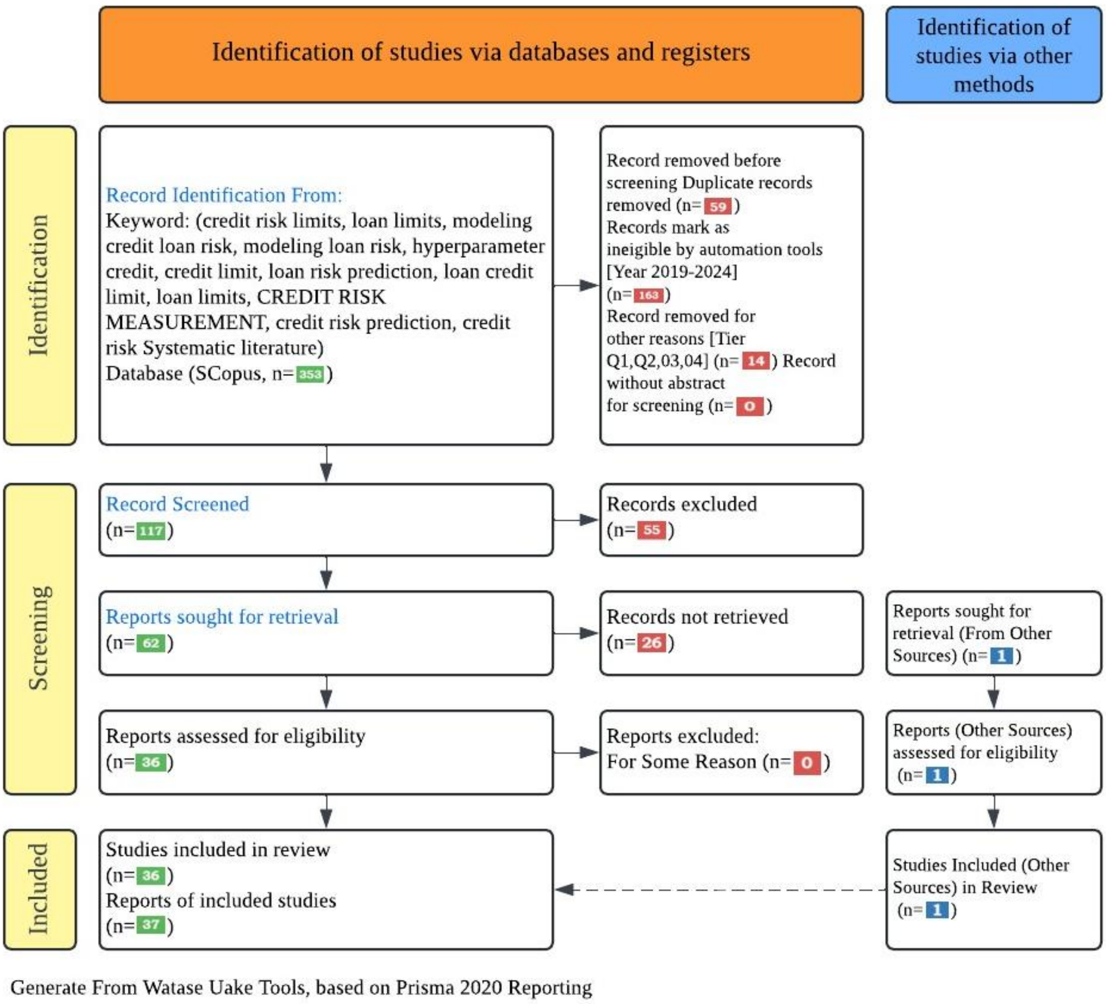

Figure 2. Prisma Flow Chart

of external factors on credit risk levels. The analysis results were then synthesized into a report or research article presenting key findings and interpretations. This synthesis enhances the understanding of credit risk and offers suggestions for further knowledge development and policy implementation in banking and finance practices.

III. Result and Discussion

The flowchart shown in Figure 2 illustrates the process of identification, screening, eligibility assessment, and inclusion of credit risk-related studies, following the PRISMA 2020 Reporting model. The process began with identifying records from the Scopus database using specific keywords, including "credit risk limits", "loan limits", "modeling credit loan risk", "hyperparameter credit", "credit limit", "loan risk prediction", "loan credit limit", "Credit Risk Measurement", "credit risk prediction", and "credit risk systematic literature", resulting in 353 records. Data cleaning followed, removing 59 duplicate records, 163 ineligible records based on publication years (2019 to 2024), and 14 records based on quality (Tiers Q1, Q2, Q3, Q4). No records were removed due to missing abstracts, leaving a total of 117 records for initial screening.

During screening, 55 of the remaining 117 records were excluded after the initial evaluation as they did not meet the predefined criteria. Sixty-two study reports were selected for retrieval and further evaluation, though 26 were not retrieved for various reasons.

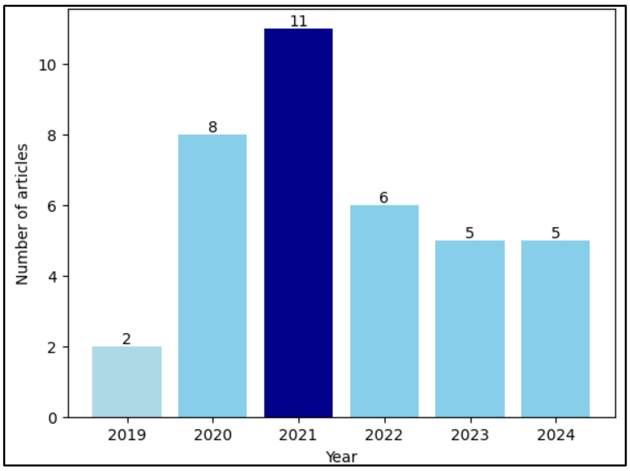

Figure 3. Distribution of Papers by Year

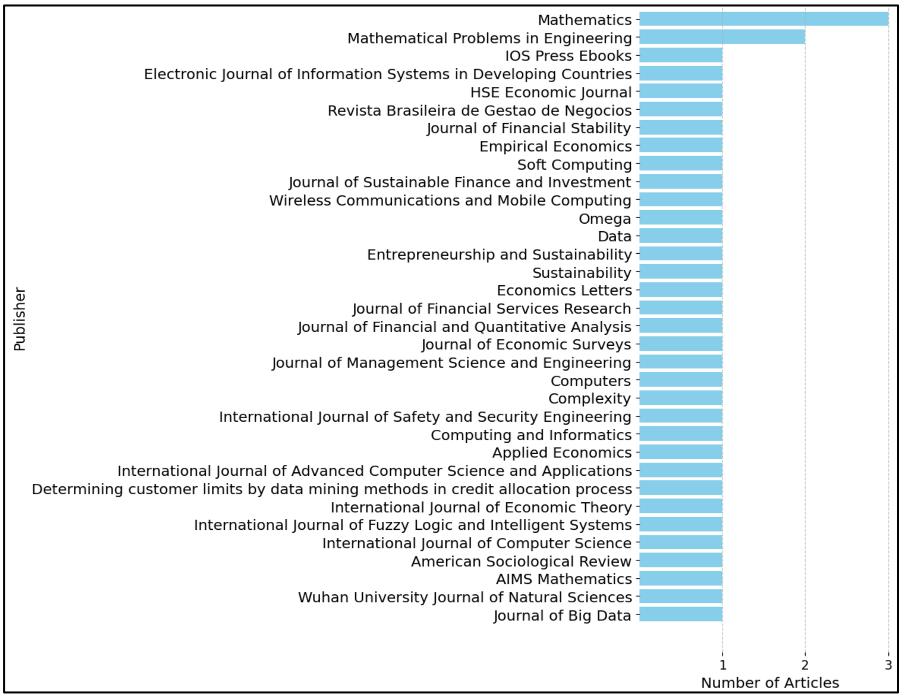

Figure 4. Journal Distribution

Of the 36 reports obtained, an in-depth eligibility assessment was conducted, with no further reports excluded. Additionally, one report from an alternative source was assessed and accepted into the review.

In total, 37 studies were included in the final review, comprising 36 studies from the main database and one from other sources. This diagram, generated using the Watase Uake tool and PRISMA 2020 reporting guidelines, offers a systematic and transparent overview of the study selection process in credit risk research, ensuring a clear and reliable methodology.

Figure 3 illustrates the distribution of studies included from 2019 to 2024, focusing on credit risk analysis in the context of determining the maximum credit limit. The bar chart reveals the variation in the number of studies conducted each year.

Figure 4 displays the distribution of studies from various journals included in the analysis, providing an overview of contributions from different literature sources to research on credit risk, particularly regarding credit limit setting. The diagram illustrates how credit risk research is distributed across journals, with some journals potentially contributing more studies than others.

TABLE 3
KEY VARIABLES

Article	Customer Income	Credit History	Loan Size	Interest Rate	Length of Payment Period	Financial Dependent	Jobs	Age	Gender
Zhao, Z.; A.G. [10]	*	*							
Ileberi, Emmanuel; [5]	*	*	*	*			*		
Yue, Zhang; [11]	*	*	*						
Meng, Pang; Zhe, Li. [12]	*		*	*					
Noha Ibrahem, Hasan; [13]	*	*		*	*				
Sara, Haloui; [4]	*	*	*						
Pegah, Sharifi; [2]	*	*	*						
Sunil, Sangwan; [14]	*	*							
Lean, Yu; Xiaoming, Zhang. [15]	*	*	*			*			
Renjing, Liu; [16]	*	*	*						
Shrikant, Kokate; [17]	*	*				*			
Eren, Duman; [3]	*	*							
Agustin, Pérez-Martín; [18]	*		*			*	*	*	
Alfredo, Martín-Oliver; [19]	*	*		*					
Jomark Pablo, Noriega; [9]	*	*				*		*	
Li, Jingming; [20]	*	*							
E., Sivasankar; [21]	*	*				*			
Tuğçe, Ayhan; [22]	*	*							
Alain, Shema [23]	*	*		*					
Alexander Sorokin [24]	*	*					*	*	
William Gatt [25]	*	*							
David, Gilchrist; Jing, Yu; Rui, Zhong [26]	*	*	*						
Victor, Pontines [27]	*	*							
Kaur Brar, J. [28]	*	*							
Barbara Kiviat [29]	*	*	*						
Gryzunova, N. V.; [6]	*	*	*						
Javier, Gomez-Biscarri; [30]	*	*	*						
Ngoc-Sang Pham [31]	*	*	*				*		
Sikha Bagui [32]	*					*	*	*	*
Ganga Aa [33]	*	*			*	*	*	*	

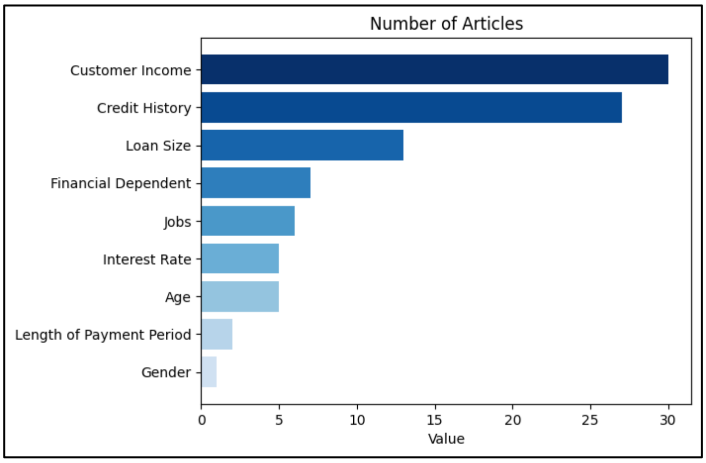

Figure 5. Number of Articles Based on Key Variables

A. *Key Attributes or Variables for Determining the Maximum Credit Loan Limit*

In studies focused on credit risk analysis, especially in determining maximum loan limits, data from 30 journals identified key variables for measuring risk and setting credit loan limits. The analysis results indicate that several variables are crucial in determining credit loan limits, including customer income, credit history, loan size, interest rate, repayment period length, financial dependents, occupation, age, and gender. Table 3 lists the articles that identify these key variables in loan limit setting.

Figure 5 shows that customer income, credit history, and loan amount are the most frequently discussed variables in the relevant literature, underscoring their importance in credit risk evaluation.

Customer income and credit history are two of the most widely considered variables in determining the maximum loan limit, as they directly indicate a customer's ability to fulfill loan repayment obligations. However, these variables often exhibit nonlinear relationships. For instance, high income does not necessarily lower credit risk if the borrower has a poor credit history. Additionally, factors such as loan size and repayment duration can modulate the impact of income and credit history. A customer with higher income might be considered low-risk if the loan size is manageable; however, a lengthy repayment period increases uncertainty around future income stability, thereby raising credit risk. This interplay among variables requires nuanced analysis, which is crucial for effective credit risk management. Customer income and loan size together are critical in determining credit limits; while higher income generally reduces credit risk, an excessively large loan size can counteract this effect [34], [35]. Thus, balancing loan size with income and repayment ability is essential to avoid overexposure to risk [36]–[38]. By assessing income levels, lenders can estimate the proportion of income available for repayments without compromising the customer's basic needs. Generally, higher income increases the likelihood of a customer qualifying for a loan with a higher limit.

Credit history reflects a customer’s past financial behavior in managing previous debts. A positive credit history indicates a track record of timely loan repayment, reducing the likelihood of future default. Conversely, a poor credit history may signal financial instability or unreliable behavior, prompting lenders to set lower loan limits to mitigate risk. Together, income and credit history provide a comprehensive picture of a customer's capacity and reliability, making them essential variables in credit risk assessment.

Additionally, factors such as interest rates and repayment duration significantly influence loan limits. Variables such as financial dependents, occupation, age, and gender also add complexity to credit risk assessment. While not included in every study, these variables illustrate the diversity in risk assessment approaches among researchers.

Below is an explanation of each key variable commonly mentioned in the literature:

1) Customer Income: Customer income is a primary variable in setting loan limits. Higher income generally indicates a greater ability to repay the loan.
2) Credit History: Credit history reflects the borrower's past record of repaying loans. A positive credit history increases lender confidence and can lead to higher loan limits.
3) Loan Size: The loan amount requested by the borrower is an important factor. A loan size that aligns with the borrower’s repayment capacity and risk profile influences the determination of loan limits.
4) Interest Rate: The interest rate applied to loans directly affects the total cost of borrowing. Higher interest rates may limit the maximum loan amount granted.
5) Length of Payment Period: The repayment period or loan term affects the size of monthly payments and is a crucial factor in setting loan limits.
6) Financial Dependents: Financial dependents, such as existing debts or family obligations (e.g., children or spouse), impact the borrower’s repayment ability and are considered when setting a safe loan limit.
7) Employment: The nature and stability of the borrower’s job can influence the loan limit. Stable employment and consistent income may support a higher loan limit.
8) Age: The borrower’s age can be significant, as younger borrowers may have a longer repayment period, while older borrowers may face future income uncertainties.
9) Gender: Although not a primary factor, gender can play a role in credit risk assessment. Differences in income or job stability between genders may be considered in some cases.

TABLE 4
MODEL

Article	Machine Learning	Neural Network	Traditional Statistics	Structural Vector Autoregression (SVAR)	Linear Regression Probability	Dynamic Stochastic General Equilibrium (DSGE)	Generalized Method of Moments (GMM)
Zhao, Z.; Cui, T.; Ding, S.; Li, J.; Bellotti, A.G. [10]	*						
Kaur Brar, J. [28]	*						
Ileberi, Emmanuel; [5]	*						
Yue, Zhang; [11]	*	*					
Meng, Pang; Zhe, Li. [12]	*						
Noha Ibrahem, Hasan; [13]			*				
Sara, Haloui; [4]			*				
Pegah, Sharifi; [2]		*					
Sunil, Sangwan; [14]			*				
Lean, Yu; Xiaoming, Zhang. [15]	*						
Renjing, Liu; [16]	*						
Shrikant, Kokate; [17]	*						
Eren, Duman; [3]	*						
Agustin, Pérez-Martín; [18]		*					
Alfredo, Martín-Oliver; [19]					*		
Jomark Pablo, Noriega; [9]							*
Li, Jingming; [20]	*						
E., Sivasankar; [21]	*						
Tuğçe, Ayhan; [22]	*						
Alexander Sorokin [24]	*						
William Gatt [25]	*						
Victor, Pontines [27]				*			
Barbara Kiviat [29]			*				
Gryzunova, N. V.; [6]						*	
Javier, Gomez-Biscarri; [30]					*		
Ngoc-Sang Pham [31]			*				
Sikha Bagui [32]	*						
Ganga Aa [33]	*						
Wenshuai, Wu [39]	*						
Valerii A., Rakhaev [40]			*				
Muhammad, Sobarsyah; [41]							*
María, Óskarsdóttir [42]	*						
Dongmei, Li; [43]	*						
Hanan Ahmed AL, Qudah [44]			*				
Fernanda Medeiros, Assef [45]	*						
Daniela, Albuquerque [46]			*				

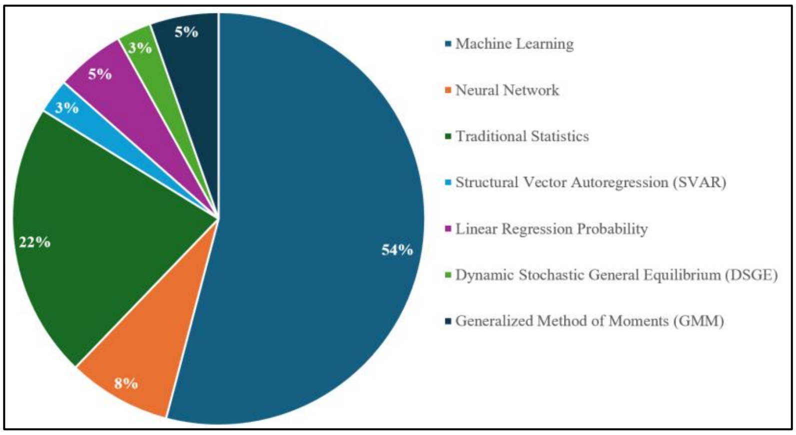

Figure 5 Percentage of Articles Based on Key Variables

B. Commonly Used Methods for Measuring Credit Risk

This study examines the methods used across various articles to determine maximum loan limits. As shown in Table 4, the diversity of methods reflects the different approaches researchers have taken to address this issue. Machine Learning methods are widely adopted due to their ability to process large, complex datasets, making them ideal for predicting credit risk in dynamic economic environments. However, traditional statistical methods, such as logistic regression, remain valuable in simpler, structured scenarios where data availability is limited. In contrast, Neural Networks, though effective in detecting intricate patterns, may be prone to overfitting with smaller datasets. Thus, the choice of method should align with the dataset's complexity and the specific goals of the risk model. Traditional statistical methods were used in 8 articles, demonstrating the continued relevance of conventional techniques in credit risk analysis. Structural Vector Autoregression (SVAR) and Linear Probability Regression were each employed in 1 article, while Dynamic Stochastic General Equilibrium (DSGE) and Generalized Method of Moments (GMM) methods were used in 2 articles each.

Figure 6 illustrates the variety of methods employed by researchers to assess credit risk and set maximum loan limits. The prevalence of Machine Learning methods highlights the growing trend of using advanced technologies in financial analysis. Of the total articles analyzed, Machine Learning methods dominate with a 54.1% share, largely due to their capability to handle complex, nonlinear datasets, making them well-suited for credit risk prediction in dynamic environments. Although Neural Networks are powerful in recognizing patterns, they face challenges like overfitting, especially in smaller datasets. Traditional statistical methods, such as logistic regression, while less flexible, offer interpretability and ease of use, making them better suited for smaller, structured datasets where model transparency is essential. Therefore, method selection should be context-dependent: Machine Learning excels in large, unstructured data environments, while traditional statistical methods are more appropriate for simpler datasets where transparency is critical.

Machine Learning has become the most widely used tool for measuring maximum loan limits due to its exceptional capability to process and analyze large volumes of complex data. This technology allows models to learn from historical data and identify patterns that may be undetectable using traditional analysis techniques. This advantage is particularly relevant in credit risk assessment, where multiple factors and variables interact in complex ways. Additionally, Machine Learning algorithms can be continuously updated and adjusted to reflect changing market conditions and customer behavior, offering greater flexibility than conventional statistical methods. As a result, the popularity and reliability of Machine Learning in managing credit risk have made it a preferred approach among researchers and practitioners for determining credit loan limits.

C. Key Issues and Limitations in Determining Credit Borrowing Limits

Determining credit borrowing limits presents a complex challenge due to various issues and limitations that require careful consideration. Key issues in setting credit loan limits include risk complexity, economic uncertainty, and the need to account for customer individuality [2], [26], [6], [33].

Assessing non-financial factors related to the client, management, economic conditions, and project activities presents a layer of complexity [13], [26], [27], [32]. These non-financial factors are often difficult to measure directly and demand a more intricate approach in credit risk analysis. For example, a client's level of education, professional experience, ongoing project activities, and the economic and market environment can all influence the client's ability to meet loan repayment obligations [13].

Setting a customer's credit limit also frequently depends on the quality of the available data [3], [10], [43], [45], [47], [48], [11], [22], [26], [33], [39]–[42]. Incomplete, inaccurate, or outdated customer data can lead to uncertainty in credit risk assessment and result in unsuitable loan limits [10], [22], [26], [39], [42]. Research shows that decisions on credit loan limits are heavily reliant on the availability of high-quality, reliable data [42], [43]. Such data enables financial institutions to make more informed decisions on credit loan limits for customers [41]–[43], [48], [49].

The uncertainty associated with regulatory or policy changes can also impact the determination of credit loan limits [10], [26], [40], [42], [44], [49]. Unexpected regulatory or policy shifts affect the risk assessment process and influence credit limit determinations, as they introduce uncertainties that must be accounted for in decision-making, potentially prompting financial institutions to adjust their lending strategies [26], [49]. These changes may involve alterations in capital requirements, supervisory rules, or credit policies issued by financial supervisory authorities [40].

Economic uncertainty also affects a customer's ability to meet loan repayment obligations, posing a limiting factor in setting credit loan limits [9], [10], [26], [33], [41], [42], [48], [49]. Unpredictable or unstable economic conditions can impact the financial stability of individuals, businesses, and industries as a whole [50], [51], [10], [42]. Economic fluctuations, market instability, and changes in macroeconomic conditions all influence the credit risk faced by banks [52], [9], [46]. Thus, economic uncertainty is a significant limiting factor in determining credit lending limits, as financial institutions must consider economic risks that could impact a customer's repayment capacity [48].

IV. Conclusion

This study presents a systematic approach to identifying key variables and measuring credit limits, highlighting major findings from the credit risk literature. The results discuss effective variables and measurement methods for determining maximum loan limits and reveal how credit limits are influenced by broader economic trends. Financial institutions must remain vigilant in adjusting credit limits in response to global economic changes, such as financial crises or periods of rapid growth. For instance, during economic downturns, institutions typically tighten credit limits due to increased uncertainty and higher default risks. Conversely, in times of economic growth, credit limits may expand as confidence in borrower stability increases. By incorporating macroeconomic indicators—such as inflation rates, unemployment levels, and GDP growth—into their credit risk models, financial institutions can enhance risk mitigation strategies and optimize loan allocation across economic cycles.

To address challenges such as economic uncertainty and data quality, financial institutions should adopt a multi-layered approach. First, continuously updating credit scoring models with real-time data from both internal and external sources can improve prediction accuracy. Second, stress-testing models under various economic scenarios can help institutions prepare for sudden market shifts. Third, employing robust data validation techniques ensures errors or gaps in customer information are flagged and resolved early in the loan approval process. These insights provide financial institutions with practical steps to mitigate risk while optimizing loan limits.

Common methods for measuring credit loan risk include Machine Learning techniques, Neural Networks, and traditional statistical approaches, with Machine Learning being the predominant choice in related literature. However, despite advancements in credit risk management, issues such as risk complexity, economic uncertainty, and suboptimal data quality remain.

Future research could expand its focus to explore the impact of external factors, such as economic conditions and regulatory changes, on loan limit determinations. Additionally, research could evaluate the effectiveness of various analytical methods for measuring credit risk and setting loan limits, while developing more accurate and reliable predictive models. Further studies are also needed to address data quality issues and improve technological applications in credit risk management. Such research is expected to provide deeper insights and more effective solutions for managing credit risk and determining appropriate credit loan limits.

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