Comprehensive Research and Reviews Journal

Journal homepage: https://crrjournals.com/crrj/

ISSN: 2961-3620 (Online)

(Research Article)

Check for updates

Conceptual framework for assessing the impact of financial access on SME growth and economic equity in the U.S

Yetunde Margaret Soremekun [1, *], Kehinde Mobolaji Abioye [2], Temitope Oluwafunmike Sanyaolu [3], Adams Gbolahan Adeleke [4] and Christianah Pelumi Efunniyi [5]

[1] *Independent Researcher, Texas USA.*
[2] *Independent Researcher, New Jersey, USA.*
[3] *Independent Researcher, UK.*
[4] *Leenit, UK.*
[5] *OneAdvanced, UK.*

Comprehensive Research and Reviews Journal, 2024, 02(01), 013–022

Publication history: Received on 03 August 2024; revised on 12 September 2024; accepted on 14 September 2024

Article DOI: https://doi.org/10.57219/crrj.2024.2.1.0026

Abstract

This review paper presents a conceptual framework for enhancing risk assessment models for small and medium-sized enterprises (SMEs) by integrating advanced analytics and machine learning techniques. The framework addresses the limitations of traditional risk models, which often fail to accurately assess the creditworthiness of SMEs due to their reliance on limited and outdated data. By incorporating diverse data sources and employing predictive modeling, the proposed framework offers a more comprehensive and dynamic approach to evaluating SME credit risk. This, in turn, facilitates greater financial inclusion by improving SMEs' access to capital, which is critical to economic growth and resilience in the United States. The paper also explores the implications for financial institutions and policymakers, emphasizing the need for regulatory support and ongoing research to maximize the benefits of these advanced risk assessment models.

Keywords: SME risk assessment; Financial Inclusion; Advanced Analytics; Machine Learning; Predictive Modeling; Economic Growth

1 Introduction

1.1 Overview of the Importance of SMEs in the U.S. Economy

Small and Medium Enterprises (SMEs) form the backbone of the U.S. economy, driving innovation, job creation, and economic growth. According to the U.S. Small Business Administration (SBA), SMEs account for many businesses in the country, employing nearly half of the private workforce (Gherghina, Botezatu, Hosszu, & Simionescu, 2020). These enterprises contribute significantly to the economy's dynamism by fostering entrepreneurship, stimulating competition, and providing diverse products and services. Their ability to adapt quickly to market changes and focus on niche markets often makes them more innovative than larger corporations. However, despite their crucial role, SMEs often face considerable challenges, particularly in accessing the financial resources necessary to sustain and grow their operations (AL-Dosari & Fetais, 2023; Asgary, Ozdemir, & Özyürek, 2020).

One of the most significant hurdles for SMEs is obtaining sufficient capital to finance their business activities. Unlike large corporations with access to a wide range of financing options, SMEs often struggle to secure loans and other forms of credit. This difficulty arises from several factors, including limited credit histories, a lack of collateral, and the higher

* Corresponding author: Yetunde Margaret Soremekun.

perceived risk associated with smaller businesses. Traditional financial institutions, such as banks, are typically risk-averse and tend to favor established, larger enterprises with strong financial records. As a result, many SMEs cannot access the funds they need to expand their operations, invest in new technologies, or even maintain day-to-day cash flow (Rahman & Khondkar, 2020).

The issue of capital access is further compounded by the relatively high costs associated with borrowing for SMEs. Interest rates and fees can be prohibitively expensive, particularly for businesses with weaker credit profiles (Abdul-Azeez, Ihechere, & Idemudia, 2024a; Kedi, Ejimuda, Idemudia, & Ijomah, 2024). Additionally, the complexity and length of the loan application process can deter SMEs from seeking financial assistance. This situation not only stifles the growth potential of these businesses but also limits their contribution to the broader economy (Huang et al., 2020).

1.2 The Need for Advanced Risk Assessment Models to Enhance Financial Inclusion

Given the challenges that SMEs face in securing capital, there is a pressing need for financial institutions to adopt more advanced and accurate risk assessment models. Traditional credit scoring methods rely heavily on historical financial data and static criteria and often fail to capture SMEs' true potential and risk profile. These models overlook qualitative factors such as the entrepreneur's experience, market conditions, and the business's innovative potential. As a result, many creditworthy SMEs are unfairly denied access to funding, contributing to financial exclusion and hampering economic development (Asgary et al., 2020; Kaira & Rześny-Cieplińska, 2019).

Advanced analytics and machine learning techniques offer a promising solution to these challenges. By leveraging large datasets and sophisticated algorithms, these technologies can provide a more nuanced and comprehensive assessment of SME credit risk. Machine learning models can analyze various variables, including non-traditional data sources such as social media activity, customer reviews, and transaction histories. This approach allows for identifying patterns and trends that may not be evident through traditional methods, leading to more accurate predictions of a business's ability to repay a loan. Furthermore, these models can continuously learn and adapt to changing economic conditions, ensuring that risk assessments remain relevant and up-to-date (Bărbuță-Mișu & Madaleno, 2020; Gherghina et al., 2020).

1.3 Purpose and Significance of the Proposed Conceptual Framework

This paper aims to develop a conceptual framework integrating advanced analytics and machine learning techniques to enhance risk assessment models specifically tailored to SMEs. This framework aims to address the limitations of traditional credit scoring methods by incorporating a broader range of data points and employing more dynamic analysis techniques. By doing so, the framework seeks to reduce the barriers to capital that SMEs face, thereby promoting financial inclusion and supporting the growth of these vital enterprises.

The significance of this framework extends beyond the immediate benefits to SMEs. By improving access to capital, the framework has the potential to stimulate economic growth, increase employment opportunities, and foster innovation across various sectors. Moreover, adopting more accurate and fair risk assessment models can lead to a more resilient financial system capable of supporting diverse businesses and contributing to overall economic stability.

2 Current Landscape of SME Risk Assessment

2.1 Traditional Risk Assessment Methods and Their Limitations

Risk assessment is critical to lending, particularly for Small and Medium Enterprises (SMEs). Traditionally, financial institutions have relied on well-established methods for assessing the creditworthiness of borrowers, typically based on historical financial data, credit scores, and collateral. While effective in many cases, these conventional models have significant limitations when applied to SMEs (Yin, Jiang, Jain, & Wang, 2020).

The most common traditional method involves credit scoring, which utilizes algorithms to evaluate a borrower's credit history, outstanding debt, and repayment behavior. For large corporations with extensive financial records, these metrics often provide a reliable indication of credit risk. However, SMEs often lack the lengthy credit histories and substantial financial documentation these models require. As a result, the risk assessment process for SMEs tends to be skewed, potentially misrepresenting these smaller enterprises' financial health and repayment capability (Kaira & Rześny-Cieplińska, 2019; Zhang, Yan, Li, Peng, & Tian, 2024).

Another limitation of traditional methods is their reliance on static data points that may not fully capture the dynamic nature of SMEs. Unlike larger companies, SMEs often experience rapid changes in their financial status, driven by market fluctuations, customer demand, or business innovations. Traditional models, which typically rely on historical data, may fail to account for these changes, leading to inaccurate risk assessments. This static approach does not consider forward-looking factors such as the potential for business growth or the entrepreneur's strategic vision, which are crucial in determining the true risk of lending to an SME (Lu, Yang, Shi, Li, & Abedin, 2022).

2.2 Overview of Existing Risk Models Used by Financial Institutions

Financial institutions have developed various risk models to assess the creditworthiness of borrowers, intending to minimize default risks while maximizing lending opportunities. The most commonly used models include the credit scorecard, Z-score, and logistic regression-based models.

The credit scorecard remains a popular tool for assessing risk, particularly in retail banking. It assigns points to different variables, such as income, employment status, and credit history, which are then aggregated to produce an overall score. This score determines the likelihood of default, with higher scores indicating lower risk. However, as previously noted, this model is often less effective for SMEs due to their unique characteristics and the lack of comprehensive credit data (Anderson, 2022; Bazarbash, 2019).

The Z-score model, another widely used tool, was initially designed to assess large corporations' bankruptcy risk. It calculates a score based on five financial ratios: profitability, leverage, liquidity, solvency, and activity. While the Z-score model has been adapted for smaller businesses, it still requires detailed financial information that many SMEs cannot readily provide. Moreover, the model's reliance on historical data makes it less responsive to real-time changes in an SME's financial condition (Asgary et al., 2020; Bazarbash, 2019; Lu et al., 2022).

Logistic regression-based models are also common in credit risk assessment. These models predict the probability of default by analyzing independent variables, such as financial ratios, macroeconomic indicators, and borrower characteristics. While logistic regression is more flexible than other methods, allowing for the inclusion of various data types, it still faces challenges when applied to SMEs. The quality and availability of data and the model's assumptions can significantly impact the accuracy of the risk predictions (do Prado, de Melo Carvalho, Carvalho de Benedicto, & Ribeiro Lima, 2019).

2.3 Challenges in Evaluating Credit Risk for SMEs

Evaluating credit risk for SMEs presents several unique challenges that are not as pronounced when dealing with larger, more established businesses. One of the primary challenges is the heterogeneity of SMEs. Unlike large corporations, which often have similar structures and financial practices, SMEs vary widely in size, industry, and business model. This diversity makes applying a one-size-fits-all approach to risk assessment difficult, as different SMEs may exhibit vastly different risk profiles (Gherghina et al., 2020; Hasan, Chy, Johora, Ullah, & Saju, 2024).

Another challenge is the limited availability of financial data. SMEs often operate with leaner financial reporting processes and may not have the resources to maintain detailed records. This lack of data makes it challenging for financial institutions to assess their creditworthiness accurately. Moreover, many SMEs are privately owned, which means their financial information is not publicly available, further complicating the risk assessment process.

The dynamic nature of SMEs also poses a challenge. As mentioned earlier, SMEs can experience rapid changes in their financial condition due to various factors, including market volatility, innovation, and shifts in consumer demand. Traditional risk models, which rely heavily on historical data, may not be equipped to capture these changes in real time, leading to potential miscalculations of risk. Furthermore, SMEs are often more susceptible to external risks such as economic downturns, regulatory environment changes, and consumer behavior shifts. These external factors can significantly impact an SME's ability to repay loans, making it difficult for financial institutions to accurately assess and price the risk of lending to these businesses (Williams & Tang, 2020; Zhao & Li, 2022).

2.4 The Role of Data Availability and Quality in Current Practices

Data availability and quality play a crucial role in the risk assessment process for SMEs. High-quality data allows for more accurate and reliable risk assessments. In contrast, poor quality or insufficient data can lead to misjudgments and higher default rates. Unfortunately, data challenges are common in the SME sector, primarily due to the abovementioned reasons. For SMEs, data availability is often limited by the scale of their operations. Unlike large corporations, which typically have robust data collection and management systems, SMEs may not have the resources to collect and analyze large volumes of data. Additionally, SMEs may operate in industries where standardized financial reporting is less common, reducing the availability of reliable data for risk assessment (Rahman & Khondkar, 2020; Williams & Tang, 2020).

The quality of data is equally important. Inaccurate or outdated data can lead to incorrect risk assessments, either the denial of credit to creditworthy SMEs or the extension of credit to high-risk businesses. Financial institutions are increasingly looking to alternative data sources, such as transaction histories, online reviews, and even social media activity, to improve the quality of data used in risk assessment. However, the integration of these non-traditional data sources into existing risk models presents its own set of challenges, including issues related to data privacy, security, and standardization (Huang et al., 2020; Kaira & Rześny-Cieplińska, 2019).

3 Integration of Advanced Analytics and Machine Learning

3.1 Advanced Analytics and Machine Learning Techniques in Risk Assessment

In recent years, advanced analytics and machine learning have emerged as powerful tools for enhancing decision-making processes across various industries. These technologies are revolutionizing risk assessment in the financial sector, particularly for Small and Medium Enterprises (SMEs). Advanced analytics involves using sophisticated techniques such as data mining, predictive modeling, and statistical analysis to extract valuable insights from large datasets. Machine learning, a subset of artificial intelligence (AI), enables systems to learn from data and improve their predictive accuracy over time without explicit programming (Paltrinieri, Comfort, & Reniers, 2019; Satipaldy, Marzhan, Zhenis, & Damira, 2021).

Integrating these technologies into risk assessment processes allows financial institutions to go beyond traditional methods, which often rely on static, historical data and limited variables. Machine learning models can analyze vast amounts of structured and unstructured data from diverse sources, identifying patterns and correlations that conventional models might overlook. Techniques such as decision trees, random forests, gradient-boosting machines, and neural networks are particularly relevant in this context. These models can handle complex, non-linear relationships between variables, making them well-suited for the nuanced and dynamic nature of SME risk profiles (Bazarbash, 2019; Kou, Chao, Peng, Alsaadi, & Herrera Viedma, 2019).

Moreover, advanced analytics techniques like natural language processing (NLP) and sentiment analysis can be used to assess qualitative data, such as customer reviews, social media posts, and news articles. This additional layer of analysis provides a more comprehensive understanding of an SME's market position and potential risks. By leveraging these advanced tools, financial institutions can develop more accurate and adaptive risk assessment models, leading to better decision-making and enhanced financial inclusion (Lantz, 2019).

Overall, the integration of advanced analytics and machine learning into risk assessment models will significantly improve the accuracy of credit risk evaluations for SMEs, leading to enhanced financial inclusion.

3.2 How Technologies Improve Credit Risk Evaluation for SMEs

Applying advanced analytics and machine learning in credit risk evaluation offers significant improvements over traditional methods, particularly in SMEs. One of the primary advantages is the ability of these technologies to process and analyze large volumes of data from various sources, including non-traditional data often overlooked in conventional risk assessments. This includes data from social media, online transactions, customer feedback, and other digital footprints, which can provide valuable insights into an SME's operational health and market behavior (Machado & Karray, 2022).

Machine learning models excel at identifying patterns and trends that are not immediately apparent through manual analysis or traditional statistical methods. For instance, a machine learning algorithm can more accurately analyze an SME's transaction history, supplier relationships, and customer interactions to predict future cash flow and repayment capacity. This capability benefits SMEs, which often lack extensive credit histories and traditional financial metrics. By incorporating non-traditional data sources and advanced algorithms, machine learning models can generate more nuanced credit scores that reflect the true risk profile of an SME (Kaira & Rześny-Cieplińska, 2019; Opute, 2020).

Additionally, machine learning models are dynamic and continuously improve over time as they are exposed to more data. This adaptability is crucial in the rapidly changing business environments that many SMEs operate within. Unlike static traditional models, which may quickly become outdated, machine learning models can adjust to new information, such as changes in market conditions or the introduction of new products and services. This real-time adaptability ensures that risk assessments remain relevant and accurate, reducing the likelihood of misclassifying creditworthy SMEs as high-risk (Zhang et al., 2024; Zhao & Li, 2022).

Moreover, advanced analytics and machine learning can reduce human bias in the credit evaluation process. Traditional credit assessments often rely on subjective judgments and predefined criteria, which can introduce bias and lead to unfair treatment of certain SMEs. In contrast, machine learning models base their predictions on objective data and consistent algorithms, minimizing the impact of human biases. This leads to a more equitable and transparent risk assessment process, improving access to capital for a broader range of SMEs (Opute, 2020; Satipaldy et al., 2021; Yin et al., 2020).

3.3 Key Components of Predictive Modeling for Financial Inclusion

Predictive modeling is a critical component of advanced analytics and machine learning in risk assessment, particularly when enhancing financial inclusion for SMEs. A well-designed predictive model integrates various data points and algorithms to forecast the likelihood of certain outcomes, such as loan repayment or default. For SMEs, predictive modeling can provide a more accurate credit risk assessment by considering many factors beyond traditional financial metrics.

Key components of predictive modeling for financial inclusion include feature selection, algorithm selection, and model validation. Feature selection involves identifying the most relevant variables that contribute to predicting credit risk. This might include financial ratios, business performance indicators, customer satisfaction scores, market trends, and social media activity in the context of SMEs. The choice of features is crucial, as it directly impacts the model's accuracy and predictive power (do Prado et al., 2019; Yin et al., 2020).

Algorithm selection is another critical component. Different machine learning algorithms have varying strengths and weaknesses, depending on the nature of the data and the specific use case. For instance, decision tree-based algorithms like random forests effectively handle complex interactions between variables. At the same time, neural networks excel in identifying patterns in large, unstructured datasets. The choice of algorithm should align with the specific characteristics of the SME data being analyzed (Anderson, 2022; Hasan et al., 2024).

Model validation tests the predictive model on a separate dataset to ensure accuracy and robustness. This step is essential to avoid overfitting, where the model performs well on the training data but fails to generalize to new, unseen data. Cross-validation techniques, such as k-fold validation, are commonly used to assess the model's performance and ensure that it provides reliable predictions (Mukhtarov, 2023; Ondolos, Tuyon, & Mohammed, 2021; Paltrinieri et al., 2019).

3.4 Potential Data Sources and the Importance of Data-Driven Decision-Making

The effectiveness of advanced analytics and machine learning in SME risk assessment depends on data availability and quality. Traditional financial data, such as balance sheets, income statements, and credit histories, remain important but are often insufficient for a comprehensive risk assessment. Financial institutions increasingly turn to alternative data sources to enhance predictive accuracy. These alternative data sources include digital transaction records, social media activity, online reviews, and mobile phone usage patterns. For example, an SME's payment history with suppliers, customer feedback on e-commerce platforms, and the frequency of online transactions can provide valuable insights into its financial health and operational stability. By incorporating these non-traditional data sources into risk models, financial institutions can gain a more holistic view of an SME's creditworthiness (Paltrinieri et al., 2019; Satipaldy et al., 2021; Zhang et al., 2024).

Data-driven decision-making is at the heart of advanced risk assessment models. Financial institutions can make more informed lending decisions by relying on objective, data-based insights rather than subjective judgments. This approach improves the accuracy of credit risk evaluations and enhances transparency and fairness in the lending process. Due to a lack of conventional financial data, SMEs that traditional models may have overlooked can now be assessed more accurately, leading to increased access to capital and greater financial inclusion. Furthermore, using real-time data in decision-making allows for more responsive risk management. In a dynamic business environment, where an SME's financial situation can change rapidly, having access to up-to-date information is crucial. Advanced analytics and machine learning enable financial institutions to monitor and reassess risk continuously, ensuring lending decisions reflect the most current and relevant data (Mukhtarov, 2023; Ondolos et al., 2021; Yin et al., 2020).

4 Conceptual Framework for Enhanced SME Risk Assessment

4.1 Detailed Description of the Proposed Framework

The proposed conceptual framework for enhanced SME risk assessment aims to bridge the gap between traditional credit evaluation methods and the dynamic, data-driven approaches made possible by advanced analytics and machine learning. This framework addresses the unique challenges SMEs face in accessing capital, such as the lack of comprehensive financial histories and the diverse nature of their operations. By leveraging a more holistic and adaptive approach to risk assessment, the framework seeks to provide a fairer and more accurate evaluation of SME creditworthiness, ultimately fostering greater financial inclusion.

At its core, the framework integrates traditional financial metrics with non-traditional data sources to create a comprehensive risk profile for each SME. This profile uses quantitative and qualitative data, including financial statements, transaction histories, market trends, customer feedback, and social media activity. By incorporating diverse data sources, the framework captures a more nuanced view of an SME's operational health, market positioning, and potential risks.

The framework is also designed to be modular and adaptable, allowing financial institutions to tailor it to the specific needs of different SMEs. This flexibility is crucial given the heterogeneity of the SME sector, where businesses vary widely in size, industry, and growth potential. The framework's modular nature enables the incorporation sector-specific risk factors, ensuring that each SME's risk assessment process is relevant and accurate.

Another key feature of the framework is its focus on real-time data analysis. Traditional risk models often rely on historical data, which may not accurately reflect the current or future state of an SME. In contrast, the proposed framework continuously updates risk profiles based on the latest available data, allowing for more timely and informed lending decisions. This dynamic approach is particularly beneficial for SMEs, whose financial conditions can change rapidly due to market shifts, innovation, or other external factors.

4.2 Integration of Analytics and Machine Learning into the Framework

Integrating advanced analytics and machine learning into the framework is fundamental to its effectiveness. These technologies enable the processing and analysis of vast amounts of data from various sources, identifying patterns and correlations that traditional methods might miss. By incorporating machine learning algorithms, the framework can continuously learn and improve over time, refining its risk assessments as more data becomes available.

The framework utilizes several machine learning techniques, including decision trees, random forests, gradient boosting, and neural networks, each offering specific advantages depending on the nature of the data being analyzed. For instance, decision trees effectively handle categorical data and make clear, interpretable decisions. At the same time, neural networks identify complex, non-linear relationships in large datasets. By leveraging these different techniques, the framework can provide a comprehensive and accurate risk assessment tailored to the specific characteristics of each SME.

Predictive modeling is central in integrating analytics and machine learning within the framework. By analyzing historical and real-time data, predictive models forecast potential outcomes, such as the likelihood of loan repayment or default. These models consider various factors, including financial ratios, market trends, customer satisfaction, and external economic indicators. The inclusion of non-traditional data sources, such as online transaction histories and social media sentiment, further enhances the accuracy of these predictions, providing a more complete picture of an SME's risk profile (Abdul-Azeez, Ihechere, & Idemudia, 2024c; Nwaimo, Adegbola, & Adegbola, 2024b; Olanrewaju, Daramola, & Ekechukwu, 2024).

Moreover, the framework incorporates natural language processing (NLP) techniques and sentiment analysis to evaluate qualitative data, such as customer reviews and social media posts. These techniques allow the framework to assess the broader market perception of an SME, which can be an important indicator of future performance. Integrating quantitative and qualitative data offers a more holistic approach to risk assessment, ensuring that all relevant factors are considered in the decision-making process (Layode et al., 2024).

4.3 Mechanisms for Reducing Barriers to Capital for SMEs

One of the primary objectives of the proposed framework is to reduce the barriers to capital that many SMEs face. Traditional risk assessment models often underestimate the creditworthiness of SMEs due to their reliance on limited financial data and static metrics. This can result in higher interest rates, reduced loan amounts, or outright denial of credit, hindering the growth and development of these businesses.

The framework addresses these issues by providing a more accurate and comprehensive assessment of SME risk. By leveraging diverse data sources and advanced analytics, the framework can identify creditworthy SMEs that traditional models might otherwise overlook. This, in turn, can lead to more favorable lending terms, such as lower interest rates and larger loan amounts, which are critical for the growth and sustainability of SMEs.

Additionally, the framework promotes financial inclusion by minimizing the impact of human bias in the credit evaluation process. Traditional credit assessments often involve subjective judgments based on predefined criteria, which can disadvantage certain SMEs, particularly those in emerging industries or those without extensive financial histories. The data-driven approach of the proposed framework ensures that lending decisions are based on objective, consistent criteria, reducing the likelihood of biased outcomes and expanding access to capital for a broader range of SMEs.

Another mechanism for reducing barriers to capital is the framework's emphasis on real-time data analysis. By continuously updating risk profiles based on the latest information, the framework allows financial institutions to make more timely and informed lending decisions. This dynamic approach is particularly beneficial in rapidly changing markets, where SMEs may experience sudden shifts in their financial conditions. By providing a more current and accurate risk assessment, the framework helps ensure that creditworthy SMEs are not unfairly penalized due to outdated or incomplete data.

4.4 Expected Outcomes and Contributions to Economic Resilience and Growth

Implementing the proposed framework will have several positive outcomes for individual SMEs and the broader economy. For SMEs, the primary benefit is improved access to capital. By providing a more accurate credit risk assessment, the framework enables financial institutions to offer more favorable lending terms, such as lower interest rates, longer repayment periods, and higher loan amounts. This increased access to capital is crucial for the growth and development of SMEs, allowing them to invest in new technologies, expand their operations, and create jobs.

On a broader scale, the framework is expected to contribute to greater economic resilience and growth. SMEs are vital to the U.S. economy, accounting for a significant share of employment and economic activity. By enhancing access to capital for these businesses, the framework supports their growth and sustainability, which drives innovation, job creation, and economic development. The increased financial inclusion of SMEs also contributes to a more diverse and resilient economy, reducing dependence on large corporations and spreading economic risk across a wider range of businesses (Abdul-Azeez, Ihechere, & Idemudia, 2024b; Nwaimo, Adegbola, & Adegbola, 2024a; Nwaimo, Adegbola, Adegbola, & Adeusi, 2024).

Furthermore, the framework's emphasis on data-driven decision-making and real-time risk assessment promotes greater transparency and efficiency in the lending process. Financial institutions can make more informed lending decisions, reducing the likelihood of defaults and improving the overall stability of the financial system. This, in turn, enhances investor confidence and encourages further investment in the SME sector, creating a positive feedback loop that supports long-term economic growth.

5 Implications for Financial Institutions and Policymakers

5.1 The Role of Financial Institutions in Adopting the Proposed Framework

Financial institutions play a pivotal role in successfully adopting the proposed framework for enhanced SME risk assessment. By integrating advanced analytics and machine learning into their risk evaluation processes, these institutions can significantly improve the accuracy and efficiency of credit assessments for SMEs. Adopting the framework requires financial institutions to invest in the necessary technology infrastructure, data management systems, and skilled personnel capable of managing and interpreting complex algorithms. Additionally, institutions must embrace a cultural shift towards data-driven decision-making, moving away from traditional, less flexible approaches. The framework can reduce the risk of loan defaults by providing a more accurate picture of an SME's financial health, ultimately leading to more sustainable lending practices and increased profitability for financial institutions.

5.2 Policy Recommendations to Support the Implementation of Advanced Risk Models

Policymakers are critical in implementing advanced risk models by creating an enabling environment that encourages innovation while ensuring fair practices. Policymakers should consider several key recommendations to support the adoption of the proposed framework. First, regulatory frameworks must be updated to accommodate advanced analytics and machine learning use in credit risk assessment. This includes providing clear guidelines on data privacy, algorithmic transparency, and the ethical use of AI. Policymakers should also promote data-sharing initiatives that allow financial institutions to access and utilize diverse data sources, which are crucial for the framework's effectiveness. Additionally, government support in the form of incentives or subsidies for financial institutions investing in these technologies could accelerate adoption. By fostering collaboration between the private sector and regulatory bodies, policymakers can ensure that implementing advanced risk models benefits SMEs and the broader economy.

The widespread adoption of the proposed framework has the potential to significantly enhance financial inclusion, particularly for SMEs that have historically faced challenges in accessing capital. By providing a more accurate and comprehensive credit risk assessment, the framework can help financial institutions identify creditworthy SMEs that traditional models may have overlooked. This increased access to capital can enable SMEs to grow, innovate, and contribute more effectively to the economy. This can lead to job creation, increased economic activity, and greater resilience in economic downturns. For the broader economy, the framework can contribute to a more diverse and stable financial system, reducing the concentration of economic power in large corporations and spreading economic risk across a wider array of businesses.

5.3 Future Directions and Areas for Further Research

While the proposed framework represents a significant advancement in SME risk assessment, several areas warrant further research and exploration. One key area is the ongoing refinement of machine learning algorithms to improve accuracy and transparency. As these technologies evolve, it will be important to ensure they remain interpretable and free from bias, particularly in credit decisions that significantly impact individuals and businesses. Additionally, further research is needed to explore integrating emerging data sources, such as real-time payment data or blockchain-based transactions, into the risk assessment process. The proposed risk assessment framework can also be adapted and applied in emerging markets, where traditional financial data may be scarce, thereby fostering financial inclusion and supporting SME growth in these regions. Another important direction for future research is the examination of the long-term impacts of this framework on financial inclusion and economic growth, particularly in different geographic and regulatory contexts. By continuing to explore these areas, researchers, financial institutions, and policymakers can ensure that the benefits of advanced risk assessment models are fully realized, contributing to a more inclusive and resilient global economy.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Abdul-Azeez, O., Ihechere, A. O., & Idemudia, C. (2024a). Digital access and inclusion for SMEs in the financial services industry through Cybersecurity GRC: A pathway to safer digital ecosystems. *Finance & Accounting Research Journal, 6*(7).

[2] Abdul-Azeez, O., Ihechere, A. O., & Idemudia, C. (2024b). Optimizing supply chain management: strategic business models and solutions using SAP S/4HANA.

[3] Abdul-Azeez, O., Ihechere, A. O., & Idemudia, C. (2024c). SMEs as catalysts for economic development: Navigating challenges and seizing opportunities in emerging markets. *GSC Advanced Research and Reviews, 19*(3), 325-335.

[4] AL-Dosari, K., & Fetais, N. (2023). Risk-management framework and information-security systems for small and medium enterprises (SMES): A meta-analysis approach. *Electronics, 12*(17), 3629.

[5] Anderson, R. A. (2022). *Credit intelligence and modelling: Many paths through the forest of credit rating and scoring*: Oxford University Press.

[6] Asgary, A., Ozdemir, A. I., & Özyürek, H. (2020). Small and medium enterprises and global risks: evidence from manufacturing SMEs in Turkey. *International Journal of Disaster Risk Science, 11*, 59-73.

[7] Bărbuţă-Mişu, N., & Madaleno, M. (2020). Assessment of bankruptcy risk of large companies: European countries evolution analysis. *Journal of risk and financial management, 13*(3), 58.

[8] Bazarbash, M. (2019). *Fintech in financial inclusion: machine learning applications in assessing credit risk*: International Monetary Fund.

[9] do Prado, J. W., de Melo Carvalho, F., Carvalho de Benedicto, G., & Ribeiro Lima, A. L. (2019). Analysis of credit risk faced by public companies in Brazil: an approach based on discriminant analysis, logistic regression and artificial neural networks. *Estudios Gerenciales, 35*(153), 347-360.

[10] Gherghina, Ș. C., Botezatu, M. A., Hosszu, A., & Simionescu, L. N. (2020). Small and medium-sized enterprises (SMEs): The engine of economic growth through investments and innovation. *Sustainability, 12*(1), 347.

[11] Hasan, R., Chy, M. A. R., Johora, F. T., Ullah, M. W., & Saju, M. A. B. (2024). Driving Growth: The Integral Role of Small Businesses in the US Economic Landscape. *American Journal of Industrial and Business Management, 14*(6), 852-868.

[12] Huang, Y., Zhang, L., Li, Z., Qiu, H., Sun, T., & Wang, X. (2020). Fintech credit risk assessment for SMEs: Evidence from China.

[13] Kaira, Z., & Rześny-Cieplińska, J. (2019). Innovation strategies in SME's economic growth and job creation in economy. *WSB Journal of business and Finance, 53*(1), 167-173.

[14] Kedi, W. E., Ejimuda, C., Idemudia, C., & Ijomah, T. I. (2024). AI software for personalized marketing automation in SMEs: Enhancing customer experience and sales. *World Journal of Advanced Research and Reviews, 23*(1), 1981-1990.

[15] Kou, G., Chao, X., Peng, Y., Alsaadi, F. E., & Herrera Viedma, E. (2019). Machine learning methods for systemic risk analysis in financial sectors.

[16] Lantz, B. (2019). *Machine learning with R: expert techniques for predictive modeling*: Packt publishing ltd.

[17] Layode, O., Naiho, H. N. N., Labake, T. T., Adeleke, G. S., Udeh, E. O., & Johnson, E. (2024). Addressing Cybersecurity Challenges in Sustainable Supply Chain Management: A Review of Current Practices and Future Directions. *International Journal of Management & Entrepreneurship Research, 6*(6), 1954-1981.

[18] Lu, Y., Yang, L., Shi, B., Li, J., & Abedin, M. Z. (2022). A novel framework of credit risk feature selection for SMEs during industry 4.0. *Annals of Operations Research*, 1-28.

[19] Machado, M. R., & Karray, S. (2022). Assessing credit risk of commercial customers using hybrid machine learning algorithms. *Expert Systems with Applications, 200*, 116889.

[20] Mukhtarov, I. (2023). Methodology of leveraging big data in financial services for enhanced decision-making. *Финансовые рынки и банки*(9), 104-115.

[21] Nwaimo, C. S., Adegbola, A. E., & Adegbola, M. D. (2024a). Predictive analytics for financial inclusion: Using machine learning to improve credit access for under banked populations. *Computer Science & IT Research Journal, 5*(6), 1358-1373.

[22] Nwaimo, C. S., Adegbola, A. E., & Adegbola, M. D. (2024b). Sustainable business intelligence solutions: Integrating advanced tools for long-term business growth.

[23] Nwaimo, C. S., Adegbola, A. E., Adegbola, M. D., & Adeusi, K. B. (2024). Evaluating the role of big data analytics in enhancing accuracy and efficiency in accounting: A critical review. *Finance & Accounting Research Journal, 6*(6), 877-892.

[24] Olanrewaju, O. I. K., Daramola, G. O., & Ekechukwu, D. E. (2024). Strategic financial decision-making in sustainable energy investments: Leveraging big data for maximum impact. *World Journal of Advanced Research and Reviews, 22*(3), 564-573.

[25] Ondolos, N. K., Tuyon, J., & Mohammed, R. U. (2021). A conceptual framework for bounded rationality in bank officers' credit decision for SME lending in Malaysia. *Asia-Pacific Management Accounting Journal (APMAJ), 16*(3), 159-189.

[26] Opute, A. P. (2020). Small and medium enterprises marketing: Innovation and sustainable economic growth perspective. In *Entrepreneurship marketing* (pp. 13-30): Routledge.

[27] Paltrinieri, N., Comfort, L., & Reniers, G. (2019). Learning about risk: Machine learning for risk assessment. *Safety science, 118*, 475-486.

[28] Rahman, M. M., & Khondkar, M. (2020). Small and medium enterprises (SME) development and economic growth of Bangladesh: A narrative of the glorious 50 years. *Barishal University Journal of Business Studies, 7*(1), 9-24.

[29] Satipaldy, B., Marzhan, T., Zhenis, U., & Damira, G. (2021). Geotechnology in the Age of AI: The Convergence of Geotechnical Data Analytics and Machine Learning. *Fusion of Multidisciplinary Research, An International Journal, 2*(1), 136-151.

[30] Williams, D., & Tang, H. (2020). Data quality management for industry 4.0: A survey. *Software Quality Professional, 22*(2), 26-35.

[31] Yin, C., Jiang, C., Jain, H. K., & Wang, Z. (2020). Evaluating the credit risk of SMEs using legal judgments. *Decision Support Systems, 136*, 113364.

[32] Zhang, W., Yan, S., Li, J., Peng, R., & Tian, X. (2024). Deep reinforcement learning imbalanced credit risk of SMEs in supply chain finance. *Annals of Operations Research*, 1-31.

[33] Zhao, J., & Li, B. (2022). Credit risk assessment of small and medium-sized enterprises in supply chain finance based on SVM and BP neural network. *Neural Computing and Applications, 34*(15), 12467-12478.