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The Impact of Using Artificial Intelligence Applications on Reducing the Default Risk in MSMEs

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Abstract: This study investigates the impact of artificial intelligence (AI) applications on reducing default risk in micro, small, and medium enterprises (MSMEs), with the aim of ensuring financial sustainability. By focusing on 450 MSMEs located in the North Al Batinah Governorate of the Sultanate of Oman, the research uses a regression model and various statistical tests to examine the relationship between AI adoption and default risk. The findings indicate that the use of AI is the most influential factor in mitigating default risk, highlighting the importance of encouraging AI adoption among MSMEs. Additionally, the perspectives of MSME owners play a significant role, suggesting that raising awareness of AI's benefits in credit risk management is essential. The study is limited to a specific region in Oman but offers valuable insights into the challenges and benefits of AI implementation in MSMEs. It recommends initiatives to shift the mindset of MSME owners toward embracing AI, as well as policies to support investment in AI tools to strengthen credit risk assessment and prevent financial distress. This research contributes to the growing body of knowledge by demonstrating how AI can reduce default rates and improve repayment performance, ultimately supporting the financial sustainability of MSMEs.

Keywords: Default Risk Prediction, Artificial Intelligence, MSMEs, Machine Learning Credit Analysis, Credit Risk, Credit Scoring Models.

Type: Research paper

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1. Introduction

The world is currently undergoing a rapid digital transformation that profoundly affects all economic sectors, including micro, small, and medium-sized enterprises (MSMEs) (Oldemeyer, 2024). As Cheraghali and Molnár (2023) point out, MSMEs play a crucial role in the global economy, representing more than 90% of businesses worldwide and making significant contributions to job creation and innovation. This highlights their importance in fostering local economic development. However, despite their vital role, MSMEs face several persistent challenges—most notably, limited access to financing and high default risk. These financial vulnerabilities often hinder their growth and long-term sustainability.

Among the most pressing challenges for MSMEs is payment risk. The consequences of default are typically more severe for smaller businesses than for larger firms due to their limited financial resilience and insufficient reserves in times of crisis. Financial risks may stem from sudden economic shifts, customer insolvency, or fluctuations in raw material prices. Therefore, MSME owners must adopt proactive measures to mitigate such risks (Mhlanga, 2021).

In this context, artificial intelligence (AI) offers numerous advantages for business operations. Loureiro et al. (2021) note that AI applications can effectively reduce repayment risk and enhance the overall financial stability of MSMEs. By leveraging AI to predict the probability of default, financial institutions can make more informed lending decisions and minimize exposure to high-risk clients, thereby protecting both MSMEs and lenders.

The concept of bankruptcy prediction has been studied since the 1930s. Altman's (1968) model marked a significant advancement by introducing multivariate analysis, replacing earlier univariate approaches. Brenes et al. (2022) highlight this as a turning point in predictive financial analytics. Further point out that conducted one of the first studies focused specifically on predicting default in small and medium-sized enterprises. Edmister noted that the lack of empirical research in this area was largely due to the difficulty in acquiring reliable data on small firms.

The global financial crisis of 2007–2009 heightened academic interest in SME failure prediction, with a noticeable increase in related studies published in 2010 compared to 2009 (Musa et al., 2025). Similarly, Farahani et al. (2022) observed that the COVID-19 pandemic significantly amplified scholarly attention in this area, with a marked rise in publications during 2021 and 2022 compared to 2020.

The rapid advancement of AI has significantly transformed the financial sector, particularly in credit risk assessment and loan default prediction. AI integration into risk management processes allows lenders to improve decision-making, reduce non-performing loans, and enhance financial stability (Brown, 2024). AI-driven risk assessment has become essential for modern financial institutions, offering improved accuracy and reduced uncertainty in lending operations.

AI technologies—including big data analytics, machine learning, and customer behavior prediction—represent powerful tools for enhancing financial risk management in MSMEs. As Dwivedi et al. (2021) demonstrate, AI-based models leverage large datasets to identify patterns, evaluate borrower creditworthiness, and predict defaults with high precision. These models significantly outperform traditional risk assessment methods. However, despite these benefits, the adoption of AI remains limited, primarily due to a lack of awareness or experience among entrepreneurs regarding its practical application (Allam & Dhunny, 2019).

Accordingly, this study aims to examine the impact of using AI applications on reducing default risk in MSMEs and maximizing financial returns to enhance financial processes. It also seeks to understand entrepreneurs' perspectives on the use of AI. The research will analyze how these applications influence financial risk management and contribute to the financial sustainability of MSMEs. Specifically, the study seeks to answer the following questions: (1) What is the impact of using artificial intelligence applications on reducing default risk among MSMEs in North Al Batinah Governorate, Sultanate of Oman? And (2) How do

MSME owners' perspectives on AI influence their decisions to adopt these technologies for reducing default risk?

2. Literature Review

For decades, predicting SME defaults has remained a significant global challenge. Numerous studies have addressed this issue within the finance literature. Ediagbonya and Tioluwani (2023) emphasized that accurate estimations of SMEs' likelihood of failure can assist policymakers in implementing restructuring strategies and refining creditworthiness scoring. Scholars such as Adeleke et al. (2019) and Wahlstrøm et al. (2024) have highlighted the importance of developing effective indicators for SME default risk to minimize lending errors.

The International Financial Corporation (IFC), a member of the World Bank Group, conducted a global survey on SME rating agencies with the aim of providing recommendations for organizing SME rating systems in developing markets. According to the IFC, an SME is considered in default if its bank account is frozen for 30 to 60 days due to failure to meet payment obligations to creditors, such as suppliers, banks, or government agencies. However, the accuracy of default risk assessment in SMEs is generally lower than that for larger corporations (Hernández-Linares et al., 2020).

Traditional default risk evaluation methods—often based on manual credit scoring—suffer from limitations in predictive accuracy (Kothandapani, 2024). Altman et al. (2023) noted that these traditional methods rely on fixed statistical parameters and historical data, which may fail to capture evolving financial behaviors and risks.

With the rise of artificial intelligence (AI) and the broader digital transformation in the financial sector, AI-driven financial decision-making has become more efficient and accurate. AI differs from other information technologies by incorporating adaptive learning, reasoning, and pattern recognition (Huang & Rust, 2021). It enables systems to simulate human-like learning and decision-making capabilities.

In the context of SMEs, one of the most impactful applications of AI in finance is the prediction of debt defaults. AI tools analyze vast amounts of financial and behavioral data to detect patterns that help forecast repayment risk (Loureiro et al., 2021). Machine learning—an essential branch of AI—uses algorithms to train models on historical data, enabling accurate predictions of customer defaults (Anil et al., 2021; Hassan et al., 2023).

Numerous studies (Kute et al., 2021; Mendhe et al., 2024; Tyagi, 2022; White, 2023) provide evidence that AI significantly contributes to reducing repayment risk in SMEs. AI enhances data analysis accuracy, helping to identify high-risk borrowers and improve lending decisions. Wei (2022) further suggested that AI can refine credit policies by assigning appropriate credit limits based on historical financial behavior, thereby reducing lending risk.

Extensive research has examined the role of AI in financial risk management and default prediction (Kothandapani, 2022). Earlier literature (Bangarigadu & Nunkoo, 2022; Fritz et al., 2022) focused on traditional models such as logistic regression and linear discriminant analysis, which formed the foundation of conventional credit scoring. However, Kothandapani (2019) observed that these models struggled with large and complex datasets.

Consequently, advances in AI have led researchers to explore machine learning techniques—including decision trees, neural networks, and deep learning algorithms—to improve predictive accuracy (Bhilare et al., 2024).

AI-powered default risk prediction offers a data-driven approach to credit risk management (Temelkov et al., 2024). By leveraging machine learning algorithms, financial institutions can analyze vast datasets and deliver real-time, high-precision risk predictions (Rodgers et al., 2023). AI models use both structured and unstructured data—including employment history, transactions, social media activity, and financial metrics—to enhance predictive capabilities. Huang et al. (2020) highlighted that integrating AI into default risk management not only improves accuracy but also helps organizations optimize their risk strategies, reduce bad debt exposure, and strengthen financial stability.

Kothandapani (2024) compared traditional credit scoring methods with AI-enhanced models and found that machine learning algorithms offered more accurate predictions by incorporating new financial trends and borrower behavior. Similarly, Cathcart et al. (2020) found that machine learning models—such as random forests and boosting techniques—outperformed traditional models in predictive accuracy.

Despite the advantages of AI in default risk prediction, several challenges remain. Ferrara (2023) identified issues such as biases in training data and regulatory concerns. Agu et al. (2024) emphasized that ethical concerns also pose barriers to the adoption of AI in credit risk modeling.

Several scholars (Kothandapani, 2020; Sadok et al., 2022; Tircovnicu & Hategan, 2023) agree on the necessity of developing unbiased AI models to promote equitable lending practices. They also stress that while AI improves predictive accuracy, financial institutions must address ethical and regulatory barriers to fully harness its potential.

In addition to these overarching concerns, MSMEs face unique challenges in implementing AI. Alirezaie et al. (2024) reported that a lack of technical knowledge among entrepreneurs remains a key obstacle. Yusof and Roslan (2023) also identified high implementation costs and concerns about privacy and data protection as major barriers. Ongoing developments in AI technology have further increased costs, limiting the accessibility of these tools for MSMEs.

Understanding MSME owners' perspectives on AI-based default risk prediction is critical. Adoption of these technologies depends heavily on entrepreneurs' awareness of their benefits. Addy et al. (2024) noted that MSME owners vary in their perceptions of AI, particularly regarding cost, implementation complexity, and risk mitigation potential. Some view AI as costly and difficult to apply, while others appreciate its potential for improving cash flow and reducing default risks (Kim et al., 2020).

Simumba et al. (2018) argued that variables related to management and employees also significantly influence SME default predictions. The strategic orientation set by management, combined with employee retention, turnover, and institutional knowledge, plays a vital role in a firm's long-term financial sustainability.

While previous research has documented the benefits of AI-based credit scoring in large institutions, few studies have explored its adoption or effectiveness from the perspective of MSME owners.

This study is novel in that it investigates the impact of AI applications on reducing default risk specifically from the standpoint of MSME owners. It bridges the gap between model-based research and user-level perspectives by exploring how those responsible for SME financial decisions perceive and apply AI technologies.

3. Methodology

This section outlines the research method, including the study population, sample, variables, data collection procedures, and statistical tests used for data analysis.

3.1. Study Variables

This study examines the dependent and independent variables by providing a theoretical analysis for each. This analysis highlights the importance of the variables and their role in the assumed relationship between the use of AI applications and reduced default risk, as well as how these variables are measured. The primary aim of this research is to study the relationship between the use of AI applications and the reduction of default risk in Omani MSMEs. The dependent variables include default risk reduction and MSME owners' perspectives.

By examining these variables, the study seeks to understand the extent to which AI adoption can enhance MSME stability and reduce default risk, thereby supporting their financial sustainability.

To ensure robustness, the research model incorporates several control variables that may also influence default risk. These include technology usage, firm size, sector of activity, years of operation, and the educational background of the owner. Including these variables helps isolate the unique effect of AI applications on default risk, accounting for potentially confounding factors.

3.2. Study Population and Sample

The study population consists of MSME retailers operating in merchandising, services, and manufacturing sectors within North Batina Governorate in the Sultanate of Oman. According to the Omani Ministry of Economy, over 6,000 MSMEs are registered in this region. A random sampling technique was used to ensure representative coverage of the target group. The targeted sample size was 480 respondents, and 450 eligible responses were retained for the final analysis.

3.3. Data Collection Techniques

Data were collected from both primary and secondary sources. Secondary data were gathered from books, journals, and specialized publications on the research topic. Primary data were collected through the distribution of an electronic questionnaire to MSME decision-makers in North Batina Governorate, aiming to assess the impact of AI application usage on MSME default risk.

3.4. Statistical Methods Used in Data Analysis

Statistical analyses were conducted to assess the reliability and validity of the questionnaire. Cronbach’s alpha coefficient was calculated for each construct, along with the Spearman-Brown split-half reliability test and item-total correlation analysis. To test the research hypotheses, multiple regression analysis was employed to examine the relationships between independent and dependent variables. Statistical indicators such as R^2, F-test, and t-test were used, with all tests conducted at a 0.05 significance level.

3.5. Cronbach's Alpha Test

Cronbach's alpha values were computed for each construct to measure internal consistency. All values in Table 1 exceeded 0.7, indicating a high level of reliability.

Table 1: Cronbach's alpha test

Construct	Cronbach Alpha	consistency
AI Usage	0.85	High
Risk Reduction	0.83	High
Business Owner Perspective	0.80	High
Control Variables	0.78	High
Spearman-Brown Reliability	0.82	

3.6. Spearman-Brown Split-Half Reliability Test

The questionnaire was divided into two halves and analyzed using the Spearman-Brown split-half reliability test. The resulting correlation coefficient was 0.82, indicating strong internal consistency in measuring the research constructs.

3.7. Item-Total Correlation Analysis

Each item's correlation with the total score of its respective construct was analyzed. All correlation values exceeded 0.3, confirming that every question contributed meaningfully to the measurement of its intended variable.

4. Results

4.1. Hypothesis Analysis Using Multiple Regression

After confirming the validity of the data for statistical analysis, the relationships between variables were tested using multiple linear regression. This analysis examined the impact of using artificial intelligence (AI) applications on reducing default risk in MSMEs in North Batina Governorate.

The coefficient of determination (R^2) was found to be 0.752, indicating that 75.2% of the variation in default risk reduction can be explained by the independent variables included in the model. This suggests that the model is robust and well-fitted.

Based on the ANOVA test in Table 2, the high F-value (45.63), which was statistically significant at $p < 0.001$, confirms that the model as a whole is effective in explaining the relationship between the dependent and independent variables. Furthermore, the large effect size (SS = 58.21 compared to SS = 19.14 for error) suggests that most of the variance in default risk is attributable to the included factors, reinforcing the role of AI in this relationship.

Table 2: ANOVA F-test

Source	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-Value	P-Value
Model	58.21	3	19.40	45.63	< 0.001
Error	19.14	476	0.040	---	---
Total	77.35	479	---	---	---

Table 3: Regression analysis

Variables	Unstandardized coefficients		T - value	Statistically significant
	β	P-value		
Constant	2.85			
AI Usage (X_1)	-0.45	0.000	-7.23	Statistically significant
Business Owner Perspective (X_2)	-0.28	0.001	-4.92	Statistically significant
Control Variables (X_3)	-0.15	0.020	-2.45	Statistically significant

Each independent variable was analyzed separately, with the following results shown in Table 3.

Hypothesis 1: There is a statistically significant direct impact of using artificial intelligence applications on reducing default risk among MSMEs in North Batina Governorate.

The regression coefficient for AI Usage (X1) indicates that a one-unit increase in AI usage corresponds to a 45% decrease in default risk. This confirms that AI significantly contributes to lowering default risk and enhancing financial stability. Therefore, the first hypothesis is accepted. This finding aligns with Altman's (1968) foundational work, which emphasized the limitations of static models for credit risk assessment. Unlike Altman's Z-score model, AI-driven approaches dynamically analyze structured and unstructured data, offering more adaptive and timely risk evaluations.

Hypothesis 2: There is a statistically significant impact of MSME owners' perspectives on AI on their decisions to reduce default risk.

The variable for Business Owner Perspective (X2) also shows a significant, albeit smaller, influence on risk reduction. This indicates that managerial attitudes and experiences play a role in AI adoption and its effectiveness. Thus, the second hypothesis is supported. This supports Loureiro et al. (2021), who found that AI and machine learning significantly enhance financial decision-making by identifying behavioral and transactional patterns. Particularly for MSMEs lacking robust financial documentation, AI offers superior predictive power.

Control variables (technology, firm size, sector, and years of operation) also show a statistically significant but weaker effect on default risk.

The regression equation can be expressed as:

$$Y = 2.85 - 0.45X_1 - 0.28X_2 - 0.15X_3 + \epsilon$$

Where: Y: Default risk reduction; X_1: AI Usage; X_2: Business Owner Perspective; X_3: Control Variables, and ϵ: Error term.

4.2. Multicollinearity Test (VIF)

Variance Inflation Factors (VIF) were computed to detect multicollinearity among independent variables. As shown in Table 4, all VIF values are below 5, indicating no multicollinearity and confirming the robustness of the regression model.

Table 4: Multicollinearity test

Variables	VIF - value
AI Usage (X_1)	2.31
Business Owner Perspective (X_2)	1.87
Control Variables (X_3)	1.52

4.3. Correlation Analysis Between Independent and Dependent Variables

Pearson correlation coefficients between independent variables and default risk reduction in Table 5 show that AI usage has the strongest negative correlation with default risk (-0.82), indicating that increased AI adoption leads to greater risk reduction. Business owner perspectives also show a strong negative correlation (-0.65), while control variables have a moderate negative correlation (-0.48).

Table 5: Correlation analysis

Variable	Correlation Coefficient with Y	P-value
AI Usage (X1)	- 0.82	< 0.001
Business Owner Perspective (X2)	- 0.65	< 0.001
Control Variables (X3)	- 0.48	< 0.05

Finally, most MSME owners are aware of the importance of using sustainable materials in product packaging. About 56% aim to maximize sales and attract consumers by reducing costs, while 25% demonstrate environmental responsibility by using eco-friendly materials, despite the absence of binding laws or government mandates.

5. Conclusion

Following the discussion of the literature related to the subject of this study, the examination of the study's hypotheses, and the presentation of the analysis results, several conclusions can be drawn.

The use of artificial intelligence emerged as the most influential factor in reducing default risk, highlighting the importance of adopting this technology in SMEs. Additionally, the perspectives of MSME owners play a significant role, indicating that raising awareness about the benefits of AI in financial risk management is crucial. Control variables were found to have a limited influence, suggesting that technological factors contribute more significantly to risk reduction than traditional factors.

Based on these conclusions, the study recommends that MSMEs should be encouraged to invest in artificial intelligence applications to improve their capacity for credit risk assessment and to avoid financial distress. By implementing these recommendations, MSMEs in North Batina Governorate in the Sultanate of Oman can enhance their liquidity management, reduce the risk of default, and leverage the benefits of AI to strengthen financial sustainability and potentially gain a competitive edge in the market.

References

Addy, W., Bello, B., Ajayi-Nifise, A., Tula, S., Odeyemi, O., & Falaiye, T. (2024). AI in credit scoring: A comprehensive review of models and predictive analytics. *Global Journal of Engineering and Technology Advances*, 18(2), 118–129. https://doi.org/10.30574/gjeta.2024.18.2.0029

Adeleke, O. K., Segun, I. B., & Olaoye, A. I. C. (2019). Impact of internal control on fraud prevention in deposit money banks in Nigeria. *Nigerian Studies in Economics and Management Sciences*, 2(1), 42–51.

Agu, E. E., Abhulimen, A. O., Obiki-Osafiele, A. N., Osundare, O. S., Adeniran, I. A., & Efunniyi, C. P. (2024). Discussing ethical considerations and solutions for ensuring fairness in AI-driven financial services. *International Journal of Frontier Research in Science*, 3(2). https://doi.org/10.56355/ijfrms.2024.3.2.0024

Allam, Z., & Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities. *Cities*, 89, 80–91. https://doi.org/10.1016/j.cities.2019.01.032

Alirezaie, M., Hoffman, W., Zabihi, P., Rahnama, H., & Pentland, A. (2024). Decentralized data and artificial intelligence orchestration for transparent and efficient small and medium-sized enterprises trade financing. *Journal of Risk and Financial Management*, 17(1), 38. https://doi.org/10.3390/jrfm17010038

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Altman, E. I., Balzano, M., Giannozzi, A., & Srhoj, S. (2023). Revisiting SME default predictors: The Omega Score. *Journal of Small Business Management*, 61(6), 2383–2417. https://doi.org/10.1080/00472778.2022.2135718

Anil, K., Sharma, S., & Mahdavi, M. (2021). Machine learning (ML) technologies for digital credit scoring in rural finance: A literature review. *Risks*, 9(11), 192. https://doi.org/10.3390/risks9110192

Bangarigadu, K., & Nunkoo, R. (2022). A success versus failure prediction model for small firms. *Journal of African Business*, 24(4), 529–545. https://doi.org/10.1080/15228916.2022.2119015

Bhilare, M., Wadajkar, V., & Kale, K. (2024). Empowering financial decisions: Precision credit scoring through advanced machine learning. *International Journal of Intelligent Systems and Applications in Engineering*, 12(13s), 155–167.

Brenes, R., Johannssen, A., & Chukhrova, N. (2022). An intelligent bankruptcy prediction model using a multilayer perceptron. *Intelligent Systems with Applications*, 16, 200136. https://doi.org/10.1016/j.iswa.2022.200136

Brown, M. (2024). Influence of artificial intelligence on credit risk assessment in banking sector. *International Journal of Modern Risk Management*, 2(1), 24–33. https://doi.org/10.47604/ijmrm.2641

Cathcart, L., Dufour, A., Rossi, L., & Varotto, S. (2020). The differential impact of leverage on the default risk of small and large firms. *Journal of Corporate Finance*, 60, 101541. https://doi.org/10.1016/j.jcorpfin.2019.101541

Cheraghali, H., & Molnár, P. (2023). SME default prediction: A systematic methodology-focused review. *Journal of Small Business Management*, 62(6), 2847–2905. https://doi.org/10.1080/00472778.2023.2277426

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Ediagbonya, V., & Tioluwani, C. (2023). The role of fintech in driving financial inclusion in developing and emerging markets: Issues, challenges and prospects. *Technological Sustainability*, 2(1), 100–119. https://doi.org/10.1108/TECHS-10-2021-0017

Farahani, M. S., Esfahani, A., Moghaddam, M. N. F., & Ramezani, A. (2022). The impact of fintech and artificial intelligence on COVID-19 and sustainable development goals. *International Journal of Innovation in Management, Economics and Social Sciences*, 2(3), 14–31. https://doi.org/10.52547/ijimes.2.3.14

Ferrara, E. (2023). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *arXiv Preprint*. https://doi.org/10.2196/preprints.48399

Fritz, S., Hein, B., & Papenbrock, J. (2022). Financial risk management and explainable, trustworthy responsible AI. *Frontiers in Artificial Intelligence*, 5, 779799. https://doi.org/10.3389/frai.2022.779799

Hassan, M., Aziz, L. A. R., & Andriansyah, Y. (2023). The role of artificial intelligence in modern banking: An exploration of AI-driven approaches for enhanced fraud prevention, risk management, and regulatory compliance. *Reviews of Contemporary Business Analytics*, 6(1), 110–132.

Hernández-Linares, R., Kellermanns, F. W., & López-Fernández, M. C. (2020). Dynamic capabilities and SME performance: The moderating effect of market orientation. *Journal of Small Business Management*, 59(1), 162–195. https://doi.org/10.1111/jsbm.12474

Huang, Y., Wang, J., Zhang, Q., & Wang, J. (2020). Fintech credit risk assessment for SMEs: Evidence from China. *IMF Working Paper*, WP/20/193. https://doi.org/10.5089/9781513557618.001

Huang, M., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Kim, B., Park, J., & Suh, J. (2020). Transparency and accountability in AI decision support: Explaining and visualizing convolutional neural networks for text information. *Decision Support Systems*, 134, 113302. https://doi.org/10.1016/j.dss.2020.113302

Kothandapani, H. P. (2024). A systematic framework for data lake curation and regulatory compliance in financial institutions: Architecture, implementation, and best practices. *Emerging Trends in Machine Intelligence and Big Data*, 16(4), 9–19. https://doi.org/10.6084/m9.figshare.28234361

Kothandapani, H. P. (2024). Automating financial compliance with AI: A new era in regulatory technology. *International Journal of Science and Research Archive*, 11(1), 2646–2659. https://doi.org/10.30574/ijsra.2024.11.1.0040

Kothandapani, H. P. (2022). Optimizing financial data governance for improved risk management and regulatory reporting in data lakes. *International Journal of Applied Machine Learning and Computational Intelligence*, 12(4), 41–63.

Kothandapani, H. P. (2019). Drivers and barriers of adopting interactive dashboard reporting in the finance sector: An empirical investigation. *Reviews of Contemporary Business Analytics*, 2(1), 45–70.

Kute, D. V., Pradhan, B., Shukla, N., & Alamri, A. (2021). Deep learning and explainable artificial intelligence techniques applied for detecting money laundering: A critical review. *IEEE Access*, 9, 82300–82317. https://doi.org/10.1109/ACCESS.2021.3086230

Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: State of the art and future research agenda. *Journal of Business Research*, 129, 911–926. https://doi.org/10.1016/j.jbusres.2020.11.001

Mendhe, V., Neema, S., & Mittal, S. (2024). Integrating algorithmic decision making into small business credit initiatives: A path to enhanced efficiency and inclusive economic growth. *International Journal of Finance*, 9(1), 54–64. https://doi.org/10.47941/ijf.1646

Mhlanga, D. (2021). Financial inclusion in emerging economies: The application of machine learning and artificial intelligence in credit risk assessment. *International Journal of Financial Studies*, 9(3), 39. https://doi.org/10.3390/ijfs9030039

Musa, H., Rech, F., Meng, F., & Musova, Z. (2025). COVID-19 impact on bankruptcy prediction for Visegrad Four manufacturing companies: A multiyear approach. In N. Tsounis & A. Vlachvei (Eds.), *Advances in Applied Macroeconomics*. Springer Proceedings in Business and Economics. Springer. https://doi.org/10.1007/978-3-031-76658-9_14

Oldemeyer, L., Jede, A., & Teuteberg, F. (2024). Investigation of artificial intelligence in SMEs: A systematic review of the state of the art and the main implementation challenges. *Management Review Quarterly*. https://doi.org/10.1007/s11301-024-00405-4

Kothandapani, H. (2020). Application of machine learning for predicting US bank deposit growth: A univariate and multivariate analysis of temporal dependencies and macroeconomic interrelationships. *Reviews of Contemporary Business Analytics*, 4, 1–20.

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review*, 33(1), 100925. https://doi.org/10.1016/j.hrmr.2022.100925

Sadok, H., Sakka, F., & El Maknouzi, M. E. H. (2022). Artificial intelligence and bank credit analysis: A review. *Cogent Economics & Finance*, 10(1), 2023262. https://doi.org/10.1080/23322039.2021.2023262

Simumba, N., Okami, S., Kodaka, A., & Kohtake, N. (2018). Alternative scoring factors using non-financial data for credit decisions in agricultural microfinance. In *IEEE International Systems Engineering Symposium (ISSE)* (pp. 1–8). https://doi.org/10.1109/SysEng.2018.8544442

Temelkov, Z., & Svrtinov, V. (2024). AI impact on traditional credit scoring models. *Journal of Economics*, 9(1). https://doi.org/10.46763/JOE249101t

Țîrcovnicu, G. I., & Hațegan, C. D. (2023). Integration of artificial intelligence in the risk management process: An analysis of opportunities and challenges. *Journal of Financial Studies*, 8(15), 198–214. https://doi.org/10.55654/JFS.2023.8.15.13

Tyagi, S. (2022). Analyzing machine learning models for credit scoring with explainable AI and optimizing investment decisions. *American International Journal of Business Management*, 5(1), 5–19.

Wei, R., & Pardo, C. (2022). Artificial intelligence and SMEs: How can B2B SMEs leverage AI platforms to integrate AI technologies? *Industrial Marketing Management*, 107, 466–483. https://doi.org/10.1016/j.indmarman.2022.10.008

Wahlstrøm, R. R., Becker, L. K., & Fornes, T. N. (2024). Enhancing credit risk assessments of SMEs with non-financial information. *Cogent Economics & Finance*, 12(1). https://doi.org/10.1080/23322039.2024.2418910

White, S. (2023, April 26). The role of artificial intelligence and machine learning in credit scoring. *CreditInfo Chronicle*. https://chronicle.creditinfo.com/2023/04/26/the-role-of-artificial-intelligence-and-machine-learning-in-credit-scoring/

Yusof, S., & Roslan, F. (2023). The impact of generative AI in enhancing credit risk modeling and decision-making in banking institutions. *Emerging Trends in Machine Intelligence and Big Data*, 15(10), 40–49.