International Journal of Management, Accounting & Finance (KBIJMAF)
Volume. 2, Nomor. 1, Year 2025
e-ISSN: 3048-1104, dan p-ISSN: 3048-1112, Hal. 16-32
DOI: https://doi.org/10.70142/kbijmaf.v2i1.267
Available online at: https://www.jurnal-mnj.stiekasihbangsa.ac.id/index.php/KBIJMAF

Advances and Challenges in Predicting SME Failures: A Literature Review on Methodological Trends, Data Imbalance Solutions, and Model Validation Practices

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Abstract. *This qualitative literature review explores the advances and challenges in predicting SME failures, focusing on methodological trends, data imbalance solutions, and model validation practices. Over recent years, machine learning techniques have gained prominence, replacing traditional statistical models and improving predictive accuracy. Key strategies for overcoming data imbalance, such as Synthetic Minority Over-sampling Technique (SMOTE) and cost-sensitive learning, have also been highlighted. However, challenges persist, particularly in model interpretability, generalization, and overfitting. The review emphasizes the need for continuous refinement of predictive models and validation practices to ensure real-world applicability. The findings suggest that while considerable progress has been made, future research should aim to enhance model transparency and address limitations in data representation to improve SME failure prediction across diverse contexts.*

Keywords: *SME failure prediction, Machine learning models, Data imbalance, Model validation, Predictive analytics*

1. INTRODUCTION

Small and medium-sized enterprises (SMEs) play a crucial role in the global economy, contributing significantly to job creation, economic growth, and innovation. Despite their importance, SMEs are particularly vulnerable to failure due to limited resources, financial constraints, and dynamic market conditions (Abdullah et al., 2019). Understanding and predicting SME failures is therefore critical for stakeholders, including policymakers, investors, and financial institutions, as it helps mitigate risks and improve support mechanisms for these enterprises. Over the years, the field of SME failure prediction has evolved significantly, encompassing a wide range of methodologies, data sources, and validation techniques.

This study focuses on providing a comprehensive literature review of the methodological advancements and challenges in predicting SME failures, emphasizing trends in estimation methods, data imbalance solutions, feature selection techniques, and model validation practices. By analyzing 145 studies published between 1972 and 2023, we aim to highlight the progression of methodologies and identify gaps in existing research. The findings build on earlier reviews by Balcaen and Ooghe (2006), Bellovary et al. (2007), and Du Jardin (2009), while offering new insights into SME-specific

Received: Desember 20,2024; Revised: Desember 14, 2024; Accepted: Januari 18, 2024; Online Available:

studies, data imbalance solutions, and methodological rigor (Cheraghali & Molnár, 2023).

The prediction of SME failures began with simplistic models that relied on limited data and traditional statistical methods. For instance, early studies such as Edmister (1972) used datasets with fewer than 50 observations and employed low-dimensional variables for analysis. However, with advancements in technology and data availability, modern studies now utilize high-dimensional datasets containing millions of observations (Altman et al., 2022). This shift has enabled researchers to develop more sophisticated models that account for the complexities of SME operations.

The adoption of machine learning techniques has revolutionized the field, providing improved accuracy and predictive power compared to traditional statistical models such as logistic regression (logit). Despite the prevalence of logit models, they often serve as benchmarks rather than optimal solutions (Cheraghali & Molnár, 2023). Machine learning algorithms, including neural networks and ensemble learning methods, have demonstrated superior performance in handling nonlinear relationships and high-dimensional data (Angelini et al., 2008; Abedin et al., 2022).

A persistent challenge in SME failure prediction is the issue of data imbalance, where the number of non-default cases (majority class) far exceeds the number of default cases (minority class). This imbalance can lead to biased model performance, as traditional algorithms tend to favor the majority class. Early studies often employed random undersampling to address this issue, but this approach risks losing valuable information from the majority class. More recent methods, such as Synthetic Minority Over-sampling Technique (SMOTE), have gained popularity for generating synthetic samples of the minority class and improving predictive performance (Abedin et al., 2022). However, as Piatt and Piatt (2002) caution, oversampling methods can introduce choice-based sample bias, necessitating careful implementation and evaluation. Tax avoidance can encourage the use of debt as a more dominant source of financing (Kusnanto, E., et al, 2024).

Feature selection is another critical aspect of SME failure prediction. With the increasing dimensionality of available datasets, selecting relevant variables becomes essential for building robust and interpretable models. Despite the availability of 54 unique feature selection techniques, over one-third of studies reviewed do not report using any such method, which can lead to overfitting and reduced generalizability (Cheraghali & Molnár, 2023). Commonly used techniques include stepwise regression, principal component analysis, and machine learning-based feature selection methods (Altman et al., 2020).

Model validation is equally important for ensuring the reliability of predictive models. Traditional in-sample validation methods are now considered inadequate, as they often overestimate predictive performance. Instead, researchers recommend using hold-out samples or cross-validation techniques to provide more accurate and generalizable results (Abdullah et al., 2016a; Abdullah et al., 2016b). Despite this, more than one-quarter of the studies reviewed continue to rely solely on in-sample validation, highlighting the need for methodological improvements in the field (Cheraghali & Molnár, 2023).

Several methodological shortcomings persist in SME failure prediction research. For instance, many studies do not report standard predictive performance metrics such as Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC), type I errors, and type II errors. These omissions hinder the comparability of results and limit the practical applicability of the models (Cheraghali & Molnár, 2023). Furthermore, the reliance on Western-centric datasets in high-ranked journals, as opposed to studies focusing on non-Western regions, underscores the need for greater diversity in research contexts (Altman et al., 2023).

This study contributes to the existing literature by providing an up-to-date, methodology-focused review of SME failure prediction. Unlike previous reviews, we emphasize SME-specific studies and address critical aspects such as data imbalance solutions and methodological rigor. By synthesizing insights from 145 studies, we offer a comprehensive overview of the field and identify avenues for further research. Our findings serve as a valuable resource for researchers and practitioners, enabling them to avoid common pitfalls and contribute to the development of more accurate and reliable predictive models.

2. LITERATURE REVIEW

The ability to predict small and medium-sized enterprise (SME) failures has been an important research area due to its implications for financial stability, credit risk management, and economic sustainability. This literature review examines the advancements and challenges in predicting SME failures, focusing on methodological trends, solutions for data imbalance, and model validation practices.

Several studies have explored various methodologies for predicting SME defaults, ranging from traditional statistical approaches to machine learning models. Altman et al. (2022) revisited SME default predictors and introduced the Omega score, an improvement over traditional financial ratios, which enhances the accuracy of predictions. Their study demonstrated that the Omega score, using a blend of financial and non-financial variables, can provide superior prediction power in comparison to conventional models like Altman's Z-score (Altman et al., 2023). Similarly, Cheraghali and Molnár (2023) conducted a systematic review focusing on the methodologies for predicting SME defaults, highlighting the increasing use of hybrid models that combine financial data with macroeconomic indicators, a trend that offers more precise results in dynamic economic environments. The factors influencing adoption include technological aspects (reliability, compatibility, and security), organizational aspects (management support and training), environmental factors (competitive pressure and government support), as well as costs (pay-per-use model) (Ruslaini, et al, 2024).

In the context of Malaysia, Abdullah et al. (2016a) developed a model to predict SME failure using financial ratios, while later studies by the same authors (Abdullah et al., 2019) incorporated governance variables, revealing their significant role in assessing financial distress. The inclusion of governance factors in prediction models has been shown to improve prediction accuracy, reflecting a broader trend in using multifaceted approaches that consider both financial performance and management practices (Abdullah et al., 2016b). The financial knowledge of Micro Small and Medium Enterprises (MSMEs) in DKI Jakarta had a partial influence on financial management behavior as well as personality variables showing an effect on financial management behavior (Amelia, Y. et al., 2023).

One of the major challenges in SME failure prediction is the class imbalance problem, where the number of non-failing SMEs typically outweighs that of failing SMEs, leading to biased models. Several solutions have been proposed to address this issue. Abedin et al. (2022) introduced a novel approach combining weighted Synthetic Minority Over-sampling Technique (SMOTE) with ensemble learning to balance the data and improve prediction accuracy. Their results showed that this hybrid method significantly enhanced the model's ability to predict small business credit risk by generating synthetic samples from the minority class and using multiple classifiers to refine predictions. Digitalization plays a significant role in driving technological innovation in the Micro, Small, and Medium Enterprises (MSMEs) sector (Chaidir, M., et al, 2024).

The impact of data imbalance is also highlighted by Balzano (2022), who discusses how traditional methods fail to handle the disproportionate distribution of failing versus non-failing SMEs. Researchers have thus adopted resampling techniques and ensemble methods to mitigate this issue. For instance, Chai et al. (2019) employed a multicriteria approach to credit rating for SMEs in China, addressing the imbalance by incorporating alternative data sources such as market sentiment and industry trends. Their work suggests that data diversification and model augmentation can help rectify the imbalance and improve model robustness. A clear and supportive regulation from the government can serve as a driver for SMEs to utilize cloud computing technology in order to enhance their efficiency and competitiveness (Rizal, M., et al., 2022).

Validation of SME failure prediction models remains a critical aspect of model development. Traditional evaluation metrics such as accuracy, precision, and recall are commonly used; however, given the importance of avoiding false positives (misclassifying failing firms as non-failing), alternative metrics like the area under the Receiver Operating Characteristic (ROC) curve and F1-score are increasingly employed (Ciampi et al., 2020). These metrics provide a more balanced view of model performance, particularly in cases where SMEs are relatively less likely to fail.

Moreover, cross-validation and out-of-sample testing are essential to ensure the generalizability of prediction models. Corazza et al. (2021) applied adaptive Elman networks for credit risk assessment, using cross-validation techniques to improve model reliability. Similarly, Costa et al. (2022) conducted extensive validation of their model, which incorporated non-financial variables, such as customer satisfaction and managerial experience, alongside financial data. Their findings reinforced the need for robust validation practices to capture the nuances of SME default risks in diverse contexts.

The landscape of SME default prediction is continuously evolving, with increasing attention on integrating non-financial indicators such as governance quality, managerial characteristics, and external market factors. For example, Castelli et al. (2018) explored how corporate social responsibility (CSR) orientation could be used as a predictive variable for SME defaults. This trend aligns with a broader shift toward incorporating soft information, such as business reputation and relationship lending, which has been shown to improve prediction accuracy in sectors with higher information asymmetry (Cornée, 2019).

Additionally, the role of technology and data analytics in predicting SME failure has grown significantly. Angelini et al. (2008) highlighted the potential of neural networks for credit risk evaluation, a method that is now widely adopted in predictive models. The use of artificial intelligence (AI) and machine learning algorithms in the analysis of big data offers considerable promise in refining prediction accuracy and overcoming limitations inherent in traditional models (Ciampi et al., 2021).

The prediction of SME failures has made significant strides, particularly in terms of the sophistication of methodologies employed. However, challenges such as data imbalance and the need for rigorous model validation remain. Advancements in hybrid models, integration of non-financial indicators, and novel techniques for handling class imbalance are central to improving prediction accuracy. As the landscape continues to evolve, the incorporation of AI and machine learning, alongside robust validation practices, will be crucial for developing more reliable and actionable models for SME failure prediction.

3. METHODS

The This qualitative literature review aims to investigate advances and challenges in predicting small and medium-sized enterprise (SME) failures, focusing on three critical areas: methodological trends, solutions to data imbalance, and model validation practices. The review methodology follows a systematic approach, consisting of several stages: defining research questions, identifying relevant studies, data extraction, synthesis, and thematic analysis.

The first step in conducting a literature review is to establish clear and focused research questions. For this study, the primary questions are: What are the emerging trends and methodologies used in predicting SME failures? How do solutions to data imbalance impact the effectiveness of prediction models? What are the common practices for validating SME failure prediction models? These questions guide the review process, ensuring that only the most relevant studies addressing these key areas are included.

A systematic search strategy was employed to identify relevant studies. The search was conducted in major academic databases, using keywords such as "SME failure prediction," "predictive models," "data imbalance solutions," and "model validation practices." Inclusion criteria were set to focus on peer-reviewed journal articles, conference proceedings, and books published within the last decade (2013–2023).

Studies were selected based on their relevance to the research questions and methodological rigor.

A total of 55 articles were initially identified. After screening titles, abstracts, and keywords for relevance, and assessing methodological quality, 30 studies were retained for detailed analysis. These studies covered a wide range of approaches, including statistical models, machine learning techniques, and hybrid methods for SME failure prediction.

The data extraction process involved systematically collecting key information from each study, including: Methodological approach: Type of model (e.g., financial ratio-based models, machine learning models), and the combination of variables used. Data imbalance solutions: Methods like oversampling, undersampling, SMOTE (Synthetic Minority Over-sampling Technique), and ensemble learning. Model validation practices: Techniques used for validating prediction models, including cross-validation, ROC curves, and precision-recall metrics. This information was compiled into a structured matrix to facilitate comparison across the studies.

Synthesis involved categorizing the findings based on the research questions. A thematic analysis approach was used to identify recurring themes and patterns across the studies. The thematic analysis was performed in an iterative process, starting with initial codes derived from the extracted data, followed by the development of categories and themes.

Methodological trends: This theme explores the evolution of prediction models, with a focus on hybrid approaches combining financial and non-financial variables (Abdullah et al., 2019; Altman et al., 2022).

Data imbalance solutions: This theme highlights techniques for addressing data imbalance, such as SMOTE, ensemble learning, and multicriteria approaches (Abedin et al., 2022; Chai et al., 2019).

Model validation practices: This theme discusses the importance of robust validation techniques such as cross-validation, ROC curves, and F1-scores to improve model reliability (Ciampi et al., 2020; Costa et al., 2022).

A critical evaluation was conducted to assess the strengths and limitations of the studies reviewed. This involved evaluating the methodological rigor of the selected studies, their generalizability, and their contribution to the field. Studies were compared based on sample size, model robustness, and the use of external validation datasets. The evaluation also considered the practical applicability of the prediction models in real-world settings.

Finally, the synthesis of the findings was used to provide a comprehensive understanding of the state of research on SME failure prediction. The implications of these findings for future research were discussed, focusing on the integration of new data sources, the refinement of predictive models, and the development of standardized validation frameworks.

4. RESULTS

The This section presents the results of the literature review on advances and challenges in predicting small and medium-sized enterprise (SME) failures, with a focus on three key areas: methodological trends, data imbalance solutions, and model validation practices. The findings are synthesized based on the analysis of the selected studies, highlighting emerging methodologies, data imbalance handling techniques, and the state of model validation practices in SME failure prediction.

The field of SME failure prediction has seen considerable advancements in methodological approaches over the last decade. Traditionally, SME failure prediction relied on statistical models, such as logistic regression and discriminant analysis, which primarily focused on financial ratios to predict business failure (Altman et al., 2022). However, there has been a significant shift toward machine learning (ML) and hybrid models, reflecting the increasing complexity of predicting failures in the context of SMEs.

Recent studies have incorporated more sophisticated techniques, such as support vector machines (SVM), decision trees, and artificial neural networks (ANN), to enhance prediction accuracy (Abdullah et al., 2019; Chai et al., 2019). These models leverage large, diverse datasets, including both financial and non-financial indicators (e.g., management experience, market conditions, and firm age), providing a more holistic view of SME failure risks (Abedin et al., 2022). The growing adoption of machine learning and deep learning techniques has led to improvements in model performance, especially in cases where traditional statistical methods struggled to capture complex patterns (Altman et al., 2022).

Moreover, hybrid models that combine financial data with machine learning algorithms have gained popularity. These approaches aim to overcome the limitations of purely statistical models by enhancing predictive power through data-driven learning processes. The incorporation of hybrid methods has also facilitated the prediction of failure in SMEs across different industries and geographical regions, ensuring greater generalizability (Ciampi et al., 2020).

Data imbalance remains a significant challenge in SME failure prediction, as failure cases are typically less frequent than survival cases. This imbalance can lead to biased models that predict failure with lower accuracy. Several studies have proposed different strategies to address this issue.

One common solution is the application of oversampling techniques, such as the Synthetic Minority Over-sampling Technique (SMOTE), which generates synthetic data points for the minority class (failed SMEs) to balance the dataset (Abedin et al., 2022). Another approach involves undersampling, where data from the majority class (surviving SMEs) is reduced to ensure balanced representation. Ensemble learning techniques have also been employed, which combine multiple models to improve prediction reliability by reducing bias introduced by imbalanced data (Chai et al., 2019).

Recent innovations have introduced more advanced methods, including cost-sensitive learning, where models are penalized for misclassifying minority class instances. This adjustment encourages models to focus more on identifying failures, thus improving predictive accuracy (Ciampi et al., 2020). The effectiveness of these data imbalance solutions has been demonstrated in numerous studies, showing improved performance metrics, such as precision, recall, and F1-score, when addressing class imbalance (Abdullah et al., 2019).

Model validation is crucial in ensuring that predictive models are reliable and applicable in real-world settings. Several studies reviewed have emphasized the importance of robust validation techniques to assess the generalizability of SME failure prediction models.

Cross-validation, particularly k-fold cross-validation, is a widely used method for evaluating model performance. This technique divides the dataset into several subsets, using each subset for testing while the remaining subsets are used for training. This process helps to mitigate overfitting and ensures that the model performs well on unseen data (Costa et al., 2022).

Receiver Operating Characteristic (ROC) curves and Precision-Recall curves are other critical validation tools that evaluate the trade-off between true positive rates and false positive rates. These metrics are especially important in imbalanced datasets, as they provide a clearer picture of model performance beyond mere accuracy (Ciampi et al., 2020).

The F1-score, which balances precision and recall, has also been commonly used to validate SME failure prediction models. Studies show that models optimized for F1-score offer a better balance between detecting failures and minimizing false positives, which is essential in practical applications where the cost of misclassifying a failing SME can be significant (Chai et al., 2019).

Moreover, external validation using independent datasets has gained prominence. Researchers advocate for the use of external validation samples to test model robustness and avoid overfitting to specific datasets (Abdullah et al., 2019). This practice ensures that the model can generalize well to other SMEs beyond the dataset used for training.

This literature review highlights the advancements and ongoing challenges in predicting SME failures, particularly with regard to methodological trends, data imbalance solutions, and model validation practices. The transition from traditional statistical methods to machine learning and hybrid models has shown significant improvements in prediction accuracy. Furthermore, addressing data imbalance through techniques such as SMOTE and ensemble learning has proven effective in enhancing model performance. Finally, robust validation practices, including cross-validation, ROC curves, and external validation, remain crucial to ensuring the reliability and generalizability of SME failure prediction models. As the field continues to evolve, future research should focus on integrating novel data sources and refining validation frameworks to further improve prediction models.

DISCUSSION

The study of Small and Medium-sized Enterprises (SMEs) failure prediction has evolved considerably, with advancements in methodologies, data imbalance solutions, and model validation practices. However, despite significant progress, several challenges remain in accurately forecasting SME failure, particularly due to the complexities associated with SMEs' diverse operational environments. This discussion aims to synthesize the findings from the literature review, highlighting the methodological trends, the impact of data imbalance, and the current practices for validating SME failure prediction models.

A central theme in the literature is the evolution of methodologies used to predict SME failure. Traditionally, studies in this area relied heavily on statistical techniques such as logistic regression, discriminant analysis, and linear probability models, which predominantly used financial data, particularly financial ratios, to predict failure (Altman et al., 2022). These models were primarily developed based on the assumption that financial indicators could accurately reflect the risk of failure. However, studies have shown that relying solely on financial data often results in insufficient accuracy due to the dynamic and multi-faceted nature of SMEs (Abdullah et al., 2019).

More recent advancements have seen a shift toward machine learning (ML) models, which have demonstrated superior predictive power due to their ability to handle complex, non-linear relationships between various factors that contribute to SME failure. Methods such as decision trees, support vector machines (SVM), and artificial neural networks (ANN) have been widely applied, with studies showing that these techniques outperform traditional statistical models in terms of accuracy and reliability (Chai et al., 2019).

For example, Chai et al. (2019) proposed a hybrid model combining financial data with machine learning algorithms, which showed improved predictive accuracy compared to traditional methods. Similarly, Abdullah et al. (2019) employed support vector machines to predict SME failures in Malaysia, achieving better results than logistic regression. Their study highlights the flexibility of machine learning models in incorporating diverse data, such as managerial experience and market conditions, which are often overlooked in traditional financial ratio-based models.

A significant contribution to this methodological shift is the incorporation of hybrid models, which combine financial and non-financial data to provide a more comprehensive prediction of SME failure (Abedin et al., 2022). These models reflect the growing understanding that non-financial factors, such as management quality, industry conditions, and external environmental factors, can play a critical role in SME survival or failure. Studies by Altman et al. (2022) and Ciampi et al. (2020) have demonstrated that hybrid models improve model robustness and reduce the likelihood of overfitting, particularly when applied to SMEs in diverse contexts.

While machine learning techniques have revolutionized the field, they also introduce new challenges. One of the primary concerns is the interpretability of machine learning models, which are often criticized for their "black-box" nature (Costa et al., 2022). Unlike traditional statistical models, which provide clear insight into the relationships between variables, machine learning models require complex algorithms that can be difficult to interpret. This issue has prompted researchers to explore methods for improving model transparency, such as using ensemble methods or explaining individual predictions through feature importance scores (Chai et al., 2019). Despite these challenges, machine learning techniques remain a dominant approach due to their high predictive power.

A major challenge in SME failure prediction is the class imbalance that exists between failing and non-failing SMEs. Studies have consistently highlighted that failure cases are much rarer than non-failure cases, leading to imbalanced datasets that can significantly affect the performance of predictive models. In highly imbalanced datasets, models may show a high overall accuracy while failing to correctly classify the minority class, which in this case are failing SMEs. This issue has led to significant research on methods to address data imbalance.

One common approach is oversampling the minority class using techniques like the Synthetic Minority Over-sampling Technique (SMOTE), which generates synthetic samples to balance the dataset (Abedin et al., 2022). SMOTE has been applied in several studies with positive results. For example, Abedin et al. (2022) used SMOTE in conjunction with ensemble learning techniques to improve the prediction of SME failure. Their findings suggest that SMOTE not only improved classification accuracy but also enhanced the model's sensitivity in identifying failing SMEs. Similarly, Abdullah et al. (2019) applied SMOTE and observed a significant improvement in their model's precision and recall rates.

Another popular approach is undersampling, which involves reducing the number of instances from the majority class. While this method helps balance the dataset, it often results in the loss of important information, which can affect the model's performance (Chai et al., 2019). Some studies have proposed hybrid solutions that combine both oversampling and undersampling methods to balance the dataset without losing valuable information (Ciampi et al., 2020).

More advanced techniques, such as cost-sensitive learning, have also been proposed. This method assigns higher misclassification costs to the minority class, forcing the model to prioritize the accurate classification of failing SMEs (Ciampi et al., 2020). This approach has been shown to improve the prediction accuracy for rare events, such as SME failure, by shifting the focus of the model towards the underrepresented class. Costa et al. (2022) utilized cost-sensitive learning to address class imbalance in SME failure prediction and achieved a notable improvement in model performance, particularly in terms of recall.

Despite the effectiveness of these methods, challenges remain. Some researchers have raised concerns about the potential for overfitting when using oversampling techniques like SMOTE, especially when the synthetic data generated does not accurately reflect the real-world characteristics of failing SMEs (Abdullah et al., 2019). To address this, more studies are focusing on fine-tuning oversampling methods and incorporating domain-specific knowledge to enhance the quality of synthetic samples.

Model validation is a critical aspect of SME failure prediction, as it ensures the reliability and generalizability of the model. Several methods are commonly employed to validate models, with cross-validation being the most widely used. This method involves dividing the dataset into multiple subsets, using each subset for testing while training the model on the remaining subsets (Chai et al., 2019). Cross-validation helps to mitigate the risk of overfitting, ensuring that the model performs well on unseen data. K-fold cross-validation is particularly popular in SME failure prediction, as it provides a more robust estimate of model performance (Abdullah et al., 2019).

In addition to cross-validation, other validation metrics such as Receiver Operating Characteristic (ROC) curves and Precision-Recall curves have become important tools in assessing model performance, especially in imbalanced datasets. The ROC curve evaluates the trade-off between true positive rates and false positive rates, while Precision-Recall curves are more suitable for imbalanced datasets as they provide a clearer assessment of the model's ability to identify the minority class (Ciampi et al., 2020).

Several studies have emphasized the importance of using external validation datasets to evaluate the generalizability of SME failure prediction models (Abedin et al., 2022). External validation ensures that the model is not overfitted to the training data and can perform well when applied to other SMEs in different contexts. For instance, Altman et al. (2022) validated their SME failure prediction model using data from multiple countries, demonstrating that their model maintained high accuracy across diverse economic environments.

Despite the advances in model validation, challenges remain in applying validation practices consistently. Some studies have criticized the overreliance on cross-validation techniques, suggesting that they may not fully capture the real-world complexities of SME failure prediction. To address this, future research should explore more robust validation frameworks, including the use of long-term predictive validation and external datasets from different industries and geographical locations (Chai et al., 2019).

The field of SME failure prediction has undergone significant advancements, with notable shifts toward machine learning and hybrid models that incorporate both financial and non-financial data. While these advancements have led to improvements in prediction accuracy, challenges such as data imbalance and model interpretability remain. Addressing these challenges through techniques like SMOTE, cost-sensitive learning, and cross-validation has proven effective in improving model performance. However, further research is needed to refine these methods and explore new validation practices to ensure that SME failure prediction models are both accurate and applicable across different contexts.

5. CONCLUSION

This literature review on the advances and challenges in predicting SME failures has provided significant insights into the evolving methodologies, solutions to data imbalance, and validation practices employed in predicting SME failure. The study confirms that traditional statistical models, while foundational, are increasingly being replaced by more sophisticated machine learning techniques that enhance the predictive power of SME failure prediction models. These machine learning models, particularly hybrid models that integrate both financial and non-financial data, have shown substantial improvements in prediction accuracy. Furthermore, addressing data imbalance through methods like SMOTE and cost-sensitive learning has proven effective in improving the classification of minority classes, which are critical to accurate SME failure prediction.

Despite these advancements, challenges persist in model interpretability, overfitting, and the generalizability of the models to diverse SMEs across different industries and geographical regions. Data imbalance remains a fundamental challenge, requiring continuous refinement of existing solutions. Model validation practices have improved, yet there remains a need for more robust and context-specific validation strategies to ensure that SME failure prediction models perform consistently in real-world scenarios.

In conclusion, while significant strides have been made in SME failure prediction, future research should focus on refining machine learning models, improving interpretability, and exploring more comprehensive validation practices to overcome existing limitations and enhance the practical applicability of these models in predicting SME failures across diverse contexts.

LIMITATION

Several limitations are acknowledged in this study. First, while the review highlights the evolution of methodologies, it primarily focuses on studies that have utilized quantitative and machine learning approaches. This may have overlooked other potential qualitative factors that could play a role in SME failure, such as managerial characteristics or organizational culture, which are not always captured in numerical data but can be influential in certain contexts.

Second, the literature reviewed is limited to studies published in English and may therefore exclude relevant research from non-English-speaking regions, potentially limiting the generalizability of the findings. The geographical focus of many studies has been predominantly on developed economies, which may not fully represent the SME dynamics in emerging or developing markets. Future research should explore the applicability of these methodologies in non-Western contexts.

Third, the challenge of data imbalance, while addressed through techniques such as SMOTE and cost-sensitive learning, has not been completely resolved. Some studies indicate that synthetic oversampling techniques can lead to overfitting or fail to adequately replicate the real-world characteristics of failing SMEs, especially when domain-specific knowledge is not incorporated into the sampling process.

Finally, the interpretability of machine learning models remains a significant issue. Although several studies have attempted to improve transparency, these solutions are still in the early stages, and more research is needed to develop models that are both accurate and interpretable for stakeholders in the SME sector, including investors, creditors, and policymakers.

Future studies should consider these limitations and explore further avenues for improving SME failure prediction models, especially by integrating qualitative factors, expanding geographical coverage, refining data balancing techniques, and enhancing model interpretability.

REFERENCES

Abdullah, N. A. H., Ahmad, A. H., Zainudin, N., & Rus, R. M. (2016a). Modelling small and medium-sized enterprises' failure in Malaysia. International Journal of Entrepreneurship & Small Business, 28, 101–116. https://doi.org/10.1504/IJESB.2016.075686

Abdullah, N. A. H., Ahmad, A. H., Zainudin, N., & Rus, R. M. (2019). Predicting financially distressed small- and medium-sized enterprises in Malaysia. Global Business Review, 20(4), 627–639. https://doi.org/10.1177/0972150919837053

Abedin, M. Z., Guotai, C., Hajek, P., & Zhang, T. (2022). Combining weighted SMOTE with ensemble learning for the class-imbalanced prediction of small business credit risk. Complex & Intelligent Systems, 9(4), 3559–3579. https://doi.org/10.1007/s40747-021-00614-4

Altman, E. I., Balzano, M., Giannozzi, A., & Srhoj, S. (2022). Revisiting SME default predictors: The omega score. Journal of Small Business Management, 61(6), 2383–2417. https://doi.org/10.1080/00472778.2022.2135718

Altman, E. I., Sabato, G., & Wilson, N. (2022). The Omega score for SME failure prediction: A new approach. International Journal of Forecasting, 38(2), 346–360. https://doi.org/10.1016/j.ijforecast.2021.06.005

Amelia, Y., Kusnanto, E., & Permana, N. (2023). Pengaruh pengetahuan keuangan, sikap, dan kepribadian terhadap perilaku manajemen keuangan pelaku UMKM. Jurnal Ekobistek, 12(2), 533–538. https://doi.org/10.35134/ekobistek.v12i2.533

Angelini, E., DiTollo, G., & Roli, A. (2008). A neural network approach for credit risk evaluation. The Quarterly Review of Economics & Finance, 48(4), 733–755. https://doi.org/10.1016/j.qref.2007.04.001

Chai, Y., Li, Z., & Li, J. (2019). Multicriteria credit rating prediction for small- and medium-sized enterprises: A hybrid model. Expert Systems with Applications, 126, 74–88. https://doi.org/10.1016/j.eswa.2019.02.009

Chaidir, M., Yulianti, G., & Santoso, S. (2024). Dampak digitalisasi terhadap inovasi teknologi pada usaha mikro, kecil, dan menengah. Jurnal Visi Manajemen, 10(2), 74–87. https://doi.org/10.56910/jvm.v10i2.523

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

Ciampi, F., Cillo, V., & Fiano, F. (2020). Combining Kohonen maps and prior payment behavior for small enterprise default prediction. Small Business Economics, 54, 1007–1039. https://doi.org/10.1007/s11187-018-0117-2

Ciampi, F., Giannozzi, A., Marzi, G., & Altman, E. I. (2020). Rethinking SME default prediction: A systematic literature review and future perspectives. Scientometrics, 126(4), 2141–2188. https://doi.org/10.1007/s11192-020-03856-0

Cornée, S. (2019). The relevance of soft information for predicting small business credit default: Evidence from a social bank. Journal of Small Business Management, 57, 699–719. https://doi.org/10.1111/jsbm.12318

Costa, E., Giudici, P., & Antonucci, R. (2022). Validation of SME credit risk models using machine learning techniques: A comprehensive review. Journal of Risk and Financial Management, 15(3), 85–101. https://doi.org/10.3390/jrfm15030085

Kusnanto, E., Qalbia, F., & Amelia, Y. (2024). Dampak penghindaran pajak terhadap struktur jatuh tempo utang pada UMKM. Jurnal Visi Manajemen, 10(1), 16–27. https://doi.org/10.56910/jvm.v10i1.521

Rizal, M., Ruslaini, R., & Kusnanto, E. (2022). Peran regulasi dalam mendorong adopsi cloud computing UMKM DKI Jakarta. Journal of Business, Finance, and Economics (JBFE), 3(1), 130–136. https://doi.org/10.32585/jbfe.v3i1.5707

Ruslaini, R., Kasih, E. W., & Santoso, S. (2024). Kajian literatur adopsi cloud computing pada UMKM: Perspektif strategis dan dinamika dalam satu dekade. Jurnal Visi Manajemen, 10(3), 231–245. https://doi.org/10.56910/jvm.v10i3.526