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# Beyond profitability: Do cash flow management indicators forecast SMEs business failure in the long run?

## Изнад профитабилности: Да ли индикатори управљања новчаним токовима предвиђају пословни неуспех МСП на дуги рок?

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**Abstract**

**Purpose:** The study examines whether cash flow management indicators can serve as reliable early predictors of small and medium-sized enterprise (SME) business failure. Specifically, it investigates the ability of cash flow–based indicators to forecast business failure three years before the initiation of formal bankruptcy proceedings.
**Methodology:** A multilayer perceptron (MLP) neural network with two hidden layers is applied to analyze a dataset of Serbian SMEs operating in the Trade and Manufacturing sectors. The model relies exclusively on cash flow indicators and is evaluated using a training–test data split and classification metrics derived from the confusion matrix.
**Findings:** The results indicate that cash flow indicators provide early signals of SME business failure three years in advance. The model demonstrates high predictive performance, achieving an area under the ROC curve (AUC) of 0.895. Indicators related to operating cash flow generation and debt-servicing capacity emerge as the most influential predictors in this sample, highlighting the importance of liquidity and sustainable cash flow management for long-term business survival.
**Originality/value:** The study contributes to the literature by focusing exclusively on cash flow indicators and applying a neural network approach to predict SME failure three years in advance. It represents one of the first regional studies combining a cash flow–centered perspective with machine learning methods and long prediction horizon, while analyzing firms within specific industry segments.
**Practical implications:** The findings offer early warning signals that can support credit risk assessment, financial monitoring, and timely interventions by managers, lenders, and policymakers.
**Limitations:** The study is limited by a relatively small sample size. While the sector-specific focus reduces structural heterogeneity, it may limit generalizability. Future research could extend the dataset across Balkan economies and incorporate additional or dynamic cash flow indicators capturing year-to-year changes.
**Keywords:** cash flow management, SMEs, neural networks, machine learning, bankruptcy prediction.
**JEL classification**: C53, C38, G33, L26, C10

**Сажетак**

**Циљ:** Циљ рада је да испита да ли индикатори управљања новчаним токовима могу послужити као поуздани рани предиктори пословног неуспеха малих и средњих предузећа (МСП). Конкретно,

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истраживање анализира способност индикатора заснованих на новчаним токовима да предвиде пословни неуспех три године пре покретања формалног стечајног поступка.
**Методологија:** У раду је примењена *„multilayer perceptron”* неуронска мрежа (ен. MLP) са два скривена слоја на узорку српских МСП из сектора трговине и прерађивачке индустрије. Модел се ослања искључиво на индикаторе новчаног тока, а његове перформансе су процењене поделом узорка на тренинг и тест скуп података, као и применом класификационих метрика изведених из матрице конфузије.
**Резултати:** Резултати указују да индикатори новчаних токова пружају ране сигнале пословног неуспеха МСП три године пре стечаја. Модел показује високе предиктивне перформансе, остварујући вредност површине испод ROC криве (AUC) од 0,895. Индикатори који се односе на генерисање оперативног новчаног тока и способност сервисирања дуга показују се као најзначајнији предиктори у овом узорку, наглашавајући значај ликвидности и одрживог управљања новчаним токовима за дугорочни опстанак предузећа.
**Оригиналност/вредност:** Рад доприноси литератури фокусирајући се искључиво на индикаторе новчаних токова и примену неуронских мрежа у предвиђању неуспеха МСП три године унапред. Такође представља једно од првих истраживања у регионалном контексту које комбинује приступ заснован на новчаним токовима са методама машинског учења, са дугим хиризонтом предикције, уз анализу предузећа у оквиру специфичних индустријских сектора.
**Практична примена:** Налази рада обезбеђују ране сигнале упозорења који могу подржати процену кредитног ризика, финансијски надзор и благовремене интервенције менаџера, кредитора и креатора економске политике.
**Ограничења истраживања:** Истраживање је ограничено релативно малим узорком. Иако фокус на одређени сектор смањује структурну хетерогеност, он може ограничити генерализовање резултата. Будућа истраживања могла би проширити скуп података на привреде Балкана и укључити додатне или динамичке индикаторе новчаних токова који прате промене из године у годину.
**Кључне речи:** управљање новчаним токовима, мала и средња предузећа, неуронске мреже, машинско учење, предвиђање стечаја.
**ЈЕЛ класификација:** C53, C38, G33, L26, C10

## Introduction

Balance sheets and income statements have traditionally served as the primary sources of information for researchers, analysts, and investors in both academic inquiry and practical decision-making. The well-known phrase “*Cash is King*” has become increasingly acknowledged and respected, reflecting the reality that it is cash (not accounting income) that ultimately sustains business activity. Cash enables firms to purchase inputs, pay salaries, service debt, and reward shareholders, making it a more direct indicator of financial resilience than accrual-based earnings. Profit-based indicators in particular may be subject to earnings management, potentially limiting their reliability as predictors of financial distress (Karas & Režňáková, 2020). This limitation may call into question the reliability of purely accrual-based models and underscores the potential benefits of incorporating alternative measures such as cash flow indicators. Managing cash flow involves overseeing the inflow and outflow of funds within a business, which affects its ability to acquire assets, remunerate staff, meet debt obligations, and maintain operational efficiency to achieve strategic goals. Often referred to as treasury management, this practice entails the careful monitoring of cash movements across a firm’s operational, financing, and investment activities (Nasimiyu, 2024). Cash represents a crucial resource for both individuals and organizations, necessary for fulfilling financial commitments and increasingly central to corporate operational strategies (Fisher, 1998). Sound cash management is vital for ensuring organizational stability, enabling future planning, and honoring obligations. Moreover, effective control over cash flows has been shown to enhance a firm's financial performance (Kroes & Manikas, 2014). The impact of small businesses on national economies is both substantial and multifaceted. Worldwide, they are regarded as key drivers of economic development, fostering entrepreneurship, innovation, and the efficient use of resources (Aren & Sibindi, 2014). In developing countries, SMEs are especially important for promoting economic growth and reducing poverty. Yet, these enterprises frequently face difficulties due to limited stakeholder awareness of effective cash flow management practices (Kongolo, 2010). For instance, in Serbia, an emerging European economy, SMEs account for 42.5% of the total business income (Business Registers Agency, 2023). The primary objective of this study is to examine and quantify the long-term capacity of cash flow indicators for predicting business failure within the SME sector in the Republic of Serbia. Specifically, the research aims to develop a classification model based on Multilayer Perceptron (MLP) neural networks (NN) to detect business failure signals three years in advance. By doing so, the study seeks to overcome the limitations of traditional models that mostly rely on accounting profitability and accrual-based metrics. Research hypothesis is defined as follows: *A predictive model based on Multilayer Perceptron (MLP) neural networks, utilizing cash flow indicators, can accurately identify business failure risk in Serbian SMEs from the Trade and Manufacturing industry three years prior to the formal initiation of bankruptcy proceedings.*

This study is organized into four sections. The first section presents a literature review, initially covering studies that utilize comprehensive financial data for predicting business failure, followed by research highlighting the specific role of cash flows. The second section, "Sample, Materials, and Methods," details the research design, including sampling strategies and methodological considerations. Statistical analysis and model development were performed using IBM SPSS Statistics. To capture complex non-linear relationships within the financial data, a Multilayer Perceptron (MLP) neural network architecture was employed. The third section presents the findings, along with the developed model and its performance evaluation. The fourth section, "Discussion", examines the advantages and limitations of the study and explores its practical implications, preceding the conclusion.

## 1. Literature review

Research on business failure and bankruptcy prediction has drawn extensively on statistical and machine learning approaches, with logistic regression, decision trees, and k-nearest neighbors among the most widely applied techniques. Early work by Ohlson (1980) marked a turning point, demonstrating that simple financial ratios such as net income to total assets and total liabilities to assets could serve as powerful predictors of bankruptcy. Since then, logistic regression has remained a benchmark method, although its performance is often outpaced by newer approaches. For instance, Papík & Papíková (2024), analyzing nearly 10,000 Slovak firms, reported that logistic regression achieved an overall accuracy of 68.3%, making it the weakest performer when compared against six alternative machine learning algorithms. Similarly, in the Serbian context, Bešlić-Obradović et al. (2018) applied logistic regression to medium and large enterprises and obtained 82.5% accuracy, while Kuster et al. (2025) developed a general log regression bankruptcy prediction model for Serbian market incorporating both financial and non-financial indicators, achieving an overall accuracy of 72.2% on the test sample for predictions three years in advance.

Decision tree models have also received significant attention. Wang et al. (2014) demonstrated the potential of DTs by developing two models on datasets of 240 and 132 firms, achieving predictive accuracies of 71.6% and 76%, respectively. Expanding this line of inquiry, Lee et al. (2020) constructed a decision tree framework using over 4,300 SMEs and showed that non-financial variables alone could deliver strong predictive power, with 82.7% accuracy on the test set. Even higher predictive performance was achieved by DiDonato & Nieddu (2015), who applied the CRT decision tree algorithm to 100 SMEs and attained 91.6% accuracy using cross-validation, relying exclusively on financial predictors. These findings highlight the flexibility of decision trees in incorporating both financial and non-financial data. In recent years, the k-nearest neighbors method has emerged as a competitive alternative. Aker & Karavardar (2023) applied k-NN models to Turkish SMEs and achieved predictive accuracies ranging from 87% to 92% for horizons of one to three years ahead, outperforming several competing approaches. Similarly, Abdullah (2021) tested k-NN on firms listed on the Dhaka Stock Exchange, finding accuracies of 82% on training data and 85% on test data, underscoring the method's robustness across different contexts. Importantly, methodological innovations have further enhanced the performance of k-NN models. For example, Smiti & Soui (2020) demonstrated that applying oversampling techniques substantially improved the AUC of k-NN predictions, raising it from as low as 0.48–0.64 to consistently strong levels of 0.86–0.86 across five-year horizons.

Inam et al. (2018) showed that neural networks can outperform traditional tools like logistic regression and discriminant analysis, requiring fewer assumptions about input variables while still delivering strong accuracy in classifying firms. Chen & Du (2009) also reported encouraging results, with their backpropagation neural network correctly predicting bankruptcy for Taiwanese companies with over 80% accuracy two years in advance. Barboza et al. (2017) investigated firms in the United States and Canada, comparing neural networks with a range of machine learning approaches. Their findings indicated that models built on indicators such as growth, size, liquidity, and profitability outperformed neural networks, which trailed by roughly 10% in predictive accuracy. Several studies have examined the role of cash flow indicators as primary predictors of business failure. Veronica et al. (2020) developed a business failure prediction model for Indonesian manufacturing companies, using a sample of 92 firms and applying logistic regression. Their findings showed that cash flow measures can reliably predict bankruptcy. Similarly, Bhandari & Iyer (2013) analyzed 100 firms, incorporating seven predictor variables into a discriminant analysis (DA) model. Four of these predictors were cash flow–based, while the remainder were derived from balance sheet and profit and loss accounts. Their matched sample design (50 failed and 50 non-failed firms) enabled the prediction of business failure one year in advance. Özcan (2020) examined business failure prediction in

Turkey, analyzing 66 firms (balanced 1:1 between solvent and failed companies) from various industries. Using logistic regression, the study developed three models to forecast bankruptcy one, two, and three years ahead, achieving accuracies of 87%, 74%, and 68%, respectively, with all predictors derived from cash flow measures. In another study, Karas & Režňáková (2020) investigated 4,350 Czech manufacturing SMEs over the period 2013–2018. Although the dataset was imbalanced (only 40 failed firms), they employed classification and regression trees (CART) and logistic regression based on 17 cash flow ratios. Best reached AUC value is 0.82. In the developed European markets, Rizzo et al. (2020) used cash flow ratios to predict bankruptcy in a couple of economies (Germany, Spain, France, Great Britain and Italy) and multiple activities (Agriculture, Industry, Services, Construction, Commerce and Food). The model has performed well across most tested countries and sectors. The results obtained are almost all adequate; in particular, in Germany and Spain, results have been particularly good, with the best AUC of 0,855 in Spanish "Industry" sector.

## 2. Sample, materials and methods

Predicting business failure is complicated by a fundamental data imbalance: the number of firms that actually experience failure (bankruptcy) is typically much smaller than those that remain solvent. This imbalance often constrains the effectiveness of predictive models in correctly identifying firms at risk (Masten & Masten, 2012). To mitigate this, prior research frequently applies a 1:1 matching strategy, constructing balanced samples of failed and solvent firms to enhance model reliability and classification accuracy (Altman, 1968; Fletcher & Goss, 1993; McKee, 1995; Cho et al., 2010; Cheong & Ramasamy, 2019). The empirical analysis in this study draws on a sample of 108 Serbian SMEs operating in Trade and Manufacturing industries. Prior models that pool firms of all sizes and sectors often overlook the unique financial dynamics of specific SMEs, which makes a sector-specific approach essential. Accordingly, the dataset here is restricted to SMEs, with equal representation of solvent firms (n=54) and failed firms (n=54), where failure is defined as the initiation of bankruptcy proceedings. Consistent with established practice (Theobald, 2021), the sample was divided into training and testing subsets using an ~80:20 ratio, including 88 SMEs in the training dataset, and 20 in the testing.

In this study, the variables are divided into dependent and independent categories. The dependent variable is defined in binary form, distinguishing between two outcomes: firms that entered bankruptcy proceedings (coded as 0) and firms that remained solvent and operational (coded as 1). The independent side is represented by nine cash flow management indicators, summarized in Table 1. These indicators serve as explanatory factors, helping to capture financial characteristics linked to a firm's probability of failure. The variables were prepared in MS Excel using data collected from publicly available financial statements, and for each firm, financial information was traced up to three years prior to its observed status (failed or solvent), which allowed capturing early signals of financial issues in the years leading up to the outcome.

*Table 1: Independent variables*

| # | Label | Calculation | Literature Source |
|---|---|---|---|
| 1 | **OCFTA** | *Operating Cash Flow / Total Assets* | Back et al. (1996), Atiya (2001), Neophytou & Molinero (2004), Ryu & Yue (2005), Abdelwahed & Amir (2005), Charitou et al. (2004), Callejón et al. (2013), Bapat & Nagale (2014), Douglas (2014), Sehgal et al. (2021), Chinedu et al. (2023) |
| 2 | **OCFTD** | *Operating Cash Flow / Total Debt* | Back et al. (1996), Ryu & Yue (2005), Alfaro (2008) |
| 3 | **OCFS** | *Operating Cash Flow / Sales* | Neophytou & Molinero (2004), Charitou et al. (2004), Bapat & Nagale (2014), Chinedu et al. (2023) |
| 4 | **CCL** | *Cash / Current Liabilities* | Back et al. (1996), Ryu & Yue (2005), Alfaro (2008), Chung et al. (2008), Zebardast et al. (2014), Fedorova et al. (2013), Inam et al. (2018) |
| 5 | **OCFCL** | *Operating Cash Flow / Current Liabilities* | Back et al. (1996), Charitou et al. (2004), Neophytou & Molinero (2004), Bapat & Nagale (2014), Lin (2009), Chinedu et al. (2023) |
| 6 | **CFNID** | *Cash Flow Net Result / Total Debt* | Leshno & Spector (1996), Virag & Kristof (2005), Brockett et al. (2006), Chen & Du (2009), Ravisankar et al. (2010), Kouki & Elkhaldi (2011), Inam et al. (2018) |
| 7 | **OCF** | *Operating Cash Flows* | Mossman et al. (1998), Anandarajan et al. (2001) |
| 8 | **CS** | *Cash / Sales* | Back et al. (1996), Lee et al. (1996), Liang et al. (2016), Brenes et al. (2022), Ryu & Yue (2005), Ravisankar et al. (2010) |
| 9 | **CFTL** | *Cash / Total Liabilities* | Back et al. (1996), Bryant (1997), Tung et al. (2004), Brenes et al. (2022) |

*Source: Author*

The modeling process was conducted using a machine learning approach based on a neural network (NN), implemented in IBM SPSS software. The predictive power of the model was evaluated using a confusion matrix and the standard performance metrics derived from it (Table 2).

*Table 2: Neural Network performance metrics*

| **Metric** | **Formula** |
|---|---|
| Accuracy | (TP + TN) / (TP + TN + FP + FN) |
| Precision | TP / (TP + FP) |
| Sensitivity (Recall) | TP / (TP + FN) |
| Specificity | TN / (TN + FP) |
| F1-Score | 2 × (Precision × Recall) / (Precision + Recall) |

| | |
|---|---|
| Negative Predictive Value (NPV) | TN / (TN + FN) |
| False Positive Rate (FPR) | FP / (FP + TN) |
| False Negative Rate (FNR) | FN / (TP + FN) |
| False Discovery Rate (FDR) | FP / (TP + FP) |
| Matthews Correlation Coefficient | (TP×TN − FP×FN) / √((TP+FP)(TP+FN)(TN+FP)(TN+FN)) |

*Source: Author*

# 3. Analysis and results

One neural network (MLP) was developed to predict SMEs failure based on cash flow management indicators ***three years in advance***. The network consists of two hidden layers, with 8 neurons in the first and 6 neurons in the second hidden layer, both including bias units. The activation functions were selected through empirical testing: the hyperbolic tangent function was applied in the hidden layers, while a sigmoid function was used in the output node. The sigmoid activation is well-suited for binary classification, as it maps the output to a probability in the (0, 1) range, and this combination yielded the best overall classification performance. The model was trained using the gradient descent algorithm with batch learning, applying an initial learning rate of 0.001 and a momentum parameter of 0.9. All the independent variables were standardized. The neural network model achieved strong predictive performance on both the training and testing datasets (Table 3). These outcomes demonstrate that cash flow–based indicators, when analyzed through a neural network, provide a reliable framework for anticipating business failure among SMEs. The boxplot (Figure 1) illustrates the distribution of predicted pseudo-probabilities generated by the neural network for failed (0) and solvent (1) SMEs. The model clearly differentiates between the two groups. For failed firms, the predicted probabilities are concentrated at higher levels for the “failed” class (blue) and substantially lower for the “solvent” class (red), with limited overlap between distributions. Conversely, solvent firms display higher predicted probabilities for the “solvent” class and markedly lower values for the “failed” class. Although some overlap and outliers are present, indicating instances where the model misclassified or was less confident, the median values and interquartile ranges demonstrate a strong separation between the two statuses. This separation suggests that the neural network, based on cash flow ratios, is effective in discriminating between solvent (healthy) and failed SMEs (that initiated bankruptcy proceedings). The relatively small degree of misalignment in predictions highlights areas for further refinement but does not detract from the overall predictive validity of the model.

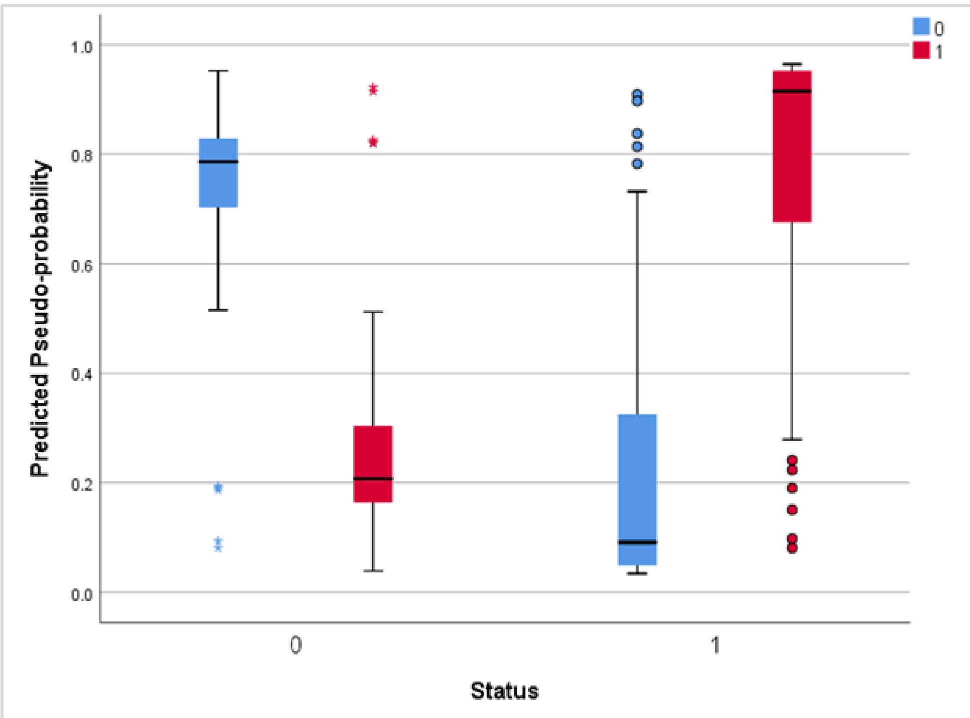
*Table 3: NN Results – assessment metrics*

| **Sample** | **Training** | **Testing** |
|---|---|---|
| *Accuracy* | *87.5%* | *85.0%* |
| *Precision* | *85.1%* | *81.8%* |
| *Sensitivity* | *90.9%* | *90.0%* |

| | | |
|---|---|---|
| *Specificity* | *84.1%* | *80.0%* |
| *F1-Score* | *87.9%* | *85.7%* |
| *Negative Predictive Value* | *90.2%* | *88.9%* |
| *False Positive Rate* | *15.9%* | *20.0%* |
| *False Negative Rate* | *9.1%* | *10.0%* |
| *False Discovery Rate* | *14.9%* | *18.2%* |
| *Matthews Correlation Coefficient* | *0.75* | *0.70* |

*Source: Author*

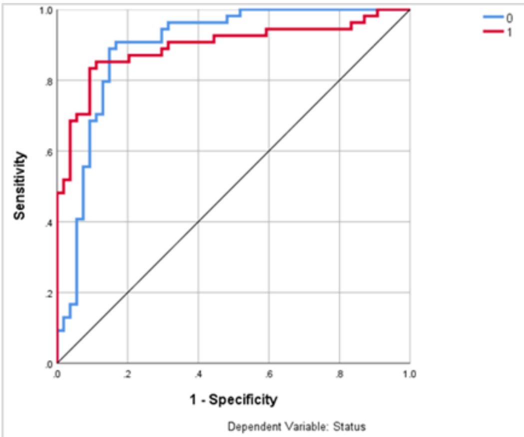
*Figure1: The Boxplot*




*Source: Author, SPSS output*

The receiver operating characteristic (ROC) curve is a widely used tool for assessing the performance of binary classification models, as it illustrates the trade-off between sensitivity and specificity (Klepáč & Hampel, 2018). The area under the curve (AUC) provides a single scalar measure that summarizes overall classification accuracy. An AUC of 0.5 indicates performance equivalent to random guessing, while a value of 1 reflects perfect classification, although the latter is rarely attainable in practice. According to established guidelines for interpreting AUC values (Al-Milli et al., 2021), the AUC score obtained for the business failure prediction model (0.895) demonstrates a high level of accuracy. The ROC curve is displayed in Figure 2. The curve for failed firms (blue, coded as 0) and the curve for solvent firms (red, coded as 1) both lie well above the diagonal line that represents random guessing. This pattern indicates that the model performs well in separating failed SMEs from those that remain solvent. The overall trajectory of curves demonstrates a favorable balance between sensitivity and specificity. Taken together, the curves confirm that the model provides reliable discriminatory power, supporting its use as an early-warning tool for failure prediction in SMEs from the Trade and Manufacturing sectors.

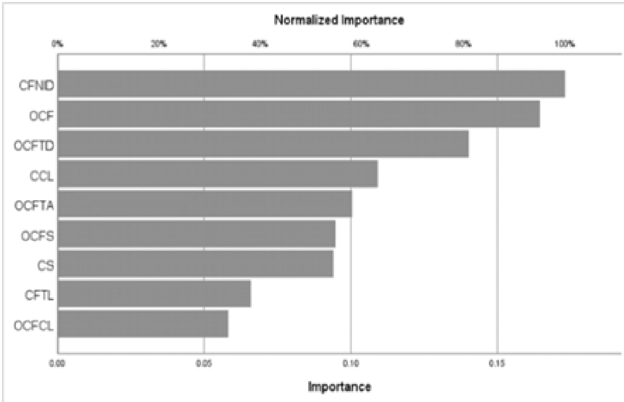
*Figure2: ROC Curve*




*Source: Author, SPSS output*

The results (Figure 3) highlight several cash flow–based indicators as the most influential predictors of business failure, providing practical insights for SME managers. The two strongest predictors, Cash Flow Net Result to Total Debt (CFNID) and Operating Cash Flow (OCF), emphasize the critical role of liquidity and debt servicing capacity. SMEs that generate insufficient cash relative to their debt obligations are at heightened risk of failure, underlining the importance of careful debt management and ensuring that operating activities consistently produce positive cash flows. Other indicators, such as Operating Cash Flow to Total Debt (OCFTD) and Cash to Current Liabilities (CCL), reinforce this point by showing that firms must be able to cover both short- and long-term obligations from internal resources rather than relying excessively on external financing. Similarly, Operating Cash Flow to Total Assets (OCFTA) signals how effectively assets are being used to generate cash, which is crucial for SMEs with limited resource bases. The importance of cash-based ratios relative to sales (OCFS and CS) suggests that revenue growth alone is insufficient; firms must ensure that sales translate into actual cash inflows, as profits may otherwise remain unrealized due to poor collection practices. Meanwhile, Cash Flow to Total Liabilities (CFTL) and Operating Cash Flow to Current Liabilities (OCFCL) underscore the necessity of balancing working capital and maintaining adequate liquidity buffers.

*Figure3: Independent variables normalized importance*




*Source: Author, SPSS output*

Taken together, these findings provide a clear message for SME managers: focusing solely on profitability indicators may overlook early warning signals of financial issues. Instead, proactive cash flow management, carefully monitoring the ability to convert sales into cash, cover liabilities, and sustain operations is vital for financial resilience. Policymakers and financial institutions can also use these insights to design more effective support mechanisms and credit assessment tools tailored to SMEs in emerging markets.

## 4. Discussion

Among the failed firms in the sample, 44 out of 54 reported at least some level of profitability (ROA ≥ 1%); 18 had ROA above 5%. This highlights an important insight: profitability alone does not safeguard firms from failure. Cash flow management should remain at the forefront of financial status assessment, complementing traditional profitability indicators.

Research results suggest that business failure can be predicted up to three years in advance relying exclusively on cash flow management indicators, using a neural network (NN) framework. The study represents a contribution to the still limited body of regional evidence on cash flow–based failure prediction in emerging European economies, where liquidity constraints and structural vulnerabilities of SMEs make such early warning tools particularly relevant. To the best of the author's knowledge, this study contributes to the literature in several ways. In contrast to several prior studies, which employ broad sets of financial ratios dominated by accrual-based measures, this work focuses exclusively on cash flow indicators as predictors of business failure. Compared with existing evidence, this research contributes by focusing on an emerging European economy. Furthermore, this cash flow model is tailored to the SME sector and further narrowed to industries particularly exposed to liquidity pressures. Moreover, the model extends the predictive horizon beyond the commonly adopted one-year benchmark in the literature, showing that early warning signals can be reliably extracted three years in advance.

From a practical perspective, the findings carry meaningful implications. For entrepreneurs and managers in SMEs, the identified indicators offer a tangible set of measures that can be tracked proactively to assess financial vulnerability well before default becomes unavoidable. Lenders, investors, and policymakers can similarly benefit from such a focused model, since cash flows directly capture repayment capacity and resilience to shocks. The simplicity of cash flow–based metrics enhances interpretability and makes the monitoring process more accessible for smaller businesses with limited analytical resources. Nevertheless, certain limitations should be acknowledged. Neural networks, while powerful in uncovering non-linear relationships, are often criticized as "black-box" models, offering limited transparency into how decisions are made. This raises challenges for adoption in professional practice, where stakeholders may demand more interpretable justifications for predictions. Future research could address this by integrating explainable AI techniques or hybrid approaches that balance predictive accuracy with transparency. Additionally, the analysis is restricted to SMEs in Serbia's trade and manufacturing sectors, which may limit generalizability. Expanding the scope across other European emerging markets would strengthen the external validity of the findings.

## Conclusion

The findings of this study suggest that business failure among SMEs can be anticipated up *to three years in advance* using exclusively cash flow management indicators analyzed through a neural network framework in Serbia. The model delivered strong results: on the training set, it achieved 87.5% accuracy. On the testing set, performance remained robust, with 85.0% accuracy. The Matthews Correlation Coefficient reached 0.75 for training and 0.70 for testing, underscoring the overall predictive validity of the model. These outcomes suggest that cash flow–based ratios, particularly those capturing liquidity and debt-servicing capacity, may provide a reliable basis for forecasting SME failure. The analysis identified several variables as the most influential predictors, including Cash Flow Net Result to Total Debt (CFNID) and Operating Cash Flow (OCF). These indicators highlight the central role of liquidity and the ability to meet debt obligations, as firms generating insufficient cash relative to their commitments faced the greatest risk of failure. Measures such as Operating Cash Flow to Total Debt (OCFTD) and Cash to Current Liabilities (CCL) further underline the importance of internal financing for both short- and long-term obligations, while ratios relative to assets or sales (OCFTA, OCFS, CS) emphasize the need for efficiency in converting operations and revenues into actual cash inflows. The findings also reveal that profitability alone cannot safeguard firms from business failure. Among failed companies, 44 out of 54 reported positive ROA ($\geq$1%), 18 had ROA above 5%. In contrast to several prior studies, this work focuses exclusively on cash flow management indicators and applies a neural network to assess their predictive power. It also extends the forecast horizon beyond the commonly adopted one-year benchmark to *three years ahead*, while tailoring the model to SMEs in Trade and Manufacturing within an emerging European economy, thereby addressing a segment that remains relatively underrepresented in the existing literature. The results *support the hypothesis $H_1$, as the MLP model* *demonstrated a high area under the ROC curve (AUC = 0.895), indicating its ability to recognize patterns of business failure in Serbian SMEs even three years in advance.*

In conclusion, the findings of this study highlight the important role of cash flow management in long-term business sustainability and contribute to the development of more focused, practical, and forward-looking tools for predicting SME failure.

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