UNIVERSIDAD & SOCIEDAD
Presentation date: February, 2025
Date of acceptance: April, 2025
Publication date: July, 2025

ASSESSING

OPERATIONAL RISKS IN MODERN FINANCIAL AND CREDIT INSTITUTIONS

EVALUACIÓN DE LOS RIESGOS OPERATIVOS EN INSTITUCIONES FINANCIERAS Y CREDITICIAS MODERNAS

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Suggested Citation (APA 7th Edition)

Makhov, I., Chumakova, E., Korneev, D., Gasparian, M. & Filyuk, M. (2025). Assessing operational risks in modern financial and credit institutions. *Universidad y Sociedad, 17*(4). e5259.

ABSTRACT

The article considers modern methods for assessing the criticality of operational risks arising from technological system failures, human errors, and organizational shortcomings. Traditional approaches, such as regression and clustering, have proven inadequate for analyzing the nonlinear and volatile nature of operational risks in the context of digital transformation. To address these challenges, an innovative approach is proposed, leveraging neural network ensembles and explainable artificial intelligence (XAI) technologies. This approach enhances the accuracy and interpretability of criticality risk forecasts. The article presents the results of previous studies in which multi-layer perceptrons (DNNs) and radial basis function networks (RBFNs) were tested for managing operational risks in credit institutions. These models demonstrated high accuracy in assessing the criticality of risks associated with human errors, Informatic Technology (IT) failures, and business process disruptions. DNNs proved effective in analyzing complex data interrelationships, while RBFNs showed high performance in classifying IT incidents. Based on these results, the further development of models using neural network ensembles is proposed to improve forecast accuracy and resilience to new data. XAI methods, such as LIME and Grad-CAM, are applied to interpret model outcomes, ensuring transparency and trust in decision-making processes. The article also outlines directions for future research and practical steps for implementing the proposed approaches in operational risk management systems.

Keywords: Operational risks, Risk criticality, Neural network ensembles, Explainable artificial intelligence, Risk management.

RESUMEN

El artículo analiza métodos modernos para evaluar la criticidad de los riesgos operativos derivados de fallos de sistemas tecnológicos, errores humanos y deficiencias organizacionales. Enfoques tradicionales, como la regresión y la agrupación en clústeres, han demostrado ser inadecuados para analizar la naturaleza no lineal y volátil de los riesgos operativos en el contexto de la transformación digital. Para abordar estos desafíos, se propone un enfoque innovador que aprovecha conjuntos de redes neuronales y tecnologías de inteligencia artificial explicable (XAI). Este enfoque mejora la precisión e interpretabilidad de los pronósticos de riesgos de criticidad. El artículo presenta los resultados de estudios previos en los que se probaron perceptrones multicapa (DNN) y redes de función de base radial (RBFN) para la gestión de riesgos operativos en entidades de crédito. Estos modelos demostraron una alta precisión en la evaluación de la criticidad de los riesgos asociados a errores humanos, fallos de Tecnología Informática (TI) e interrupciones de los procesos de negocio. Las DNN demostraron ser eficaces en el análisis de interrelaciones complejas de datos, mientras que las RBFN mostraron un alto rendimiento en la clasificación de incidentes de TI. Con base en estos resultados, se propone el desarrollo de modelos que utilicen conjuntos de redes neuronales para mejorar la precisión de los pronósticos y la resiliencia a nuevos datos. Se aplican métodos XAI, como LIME y Grad-CAM, para interpretar los resultados de los modelos, garantizando la transparencia y la confianza en los procesos de toma de decisiones. El artículo también describe las líneas de investigación futuras y los pasos prácticos para implementar los enfoques propuestos en los sistemas de gestión de riesgos operacionales.

Palabras clave: Riesgos operacionales, Criticidad del riesgo, Conjuntos de redes neuronales, Inteligencia artificial explicable, Gestión de riesgos.

INTRODUCTION

In modern financial and credit institutions, assessing operational risks is becoming increasingly critical (Allen & Gale, 2010). Operational risks refer to the risk of losses arising from IT infrastructure failures, human errors, procedural violations, non-compliance with legal requirements, and external factors. These risks are challenging to analyze and predict due to their wide range, encompassing technological and cyber risks, human errors, and external threats (Peyhani, 2022). These factors are often interconnected and exhibit non-linear dependencies, complicating their analysis through traditional methods.

Operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, personnel, systems, or external events. It includes a wide range of risks, such as processing errors, fraud, legal issues, business interruptions, cybersecurity, and natural disasters.

Assessing operational risks in modern financial and credit institutions involves identifying, analyzing, and mitigating risks that may arise from internal errors, system failures, external events, and other factors that could impact the institution's operations and results. This process is crucial to protecting the institutions' financial stability, reputation, and regulatory compliance.

Operational risks can be classified into several main categories:

Technological risks are risks associated with IT infrastructure failures, cyberattacks, and data breaches (Peyhani, 2022);

Personnel risks are risks stemming from employee errors, intentional misconduct, or disciplinary violations, leading to adverse outcomes (Chumakova et al., 2024a);

Organizational risks are risks caused by deficiencies in business processes, procedural violations, and insufficient oversight;

Compliance risks are risks related to non-compliance with laws, regulations, or internal company policies, which may result in fines and reputational damage;

External risks are risks arising from external factors, such as changes in legislation, macroeconomic instability, or natural disasters, which are beyond the organization's control;

Financial and reporting risks are risks linked to errors in financial reporting, data inaccuracies, and accounting mistakes that can impact financial results and reputation.

For financial and credit institutions, assessing these risks is particularly significant as incidents related to technological failures or human errors can result in substantial financial losses and reputational damage. With increasing automation, such events demand precise evaluation and swift response (Ashby, 2022). The Central Bank of the Russian Federation and the Basel Committee on Banking Supervision emphasize the need for rigorous control of operational risks, necessitating the development of more accurate and interpretable models for their assessment.

This study aims to develop methods for assessing the criticality of operational risks using neural network ensembles and explainable artificial intelligence (XAI) technologies. Neural network ensembles, which combine the predictions of multiple models, enable greater accuracy and resilience to volatile data, making this approach particularly suitable for analyzing technological, personnel, and organizational risks. The application of XAI for interpreting the decisions of such models ensures transparency in the forecasting process and allows for an understanding of how the model arrived at its assessment of risk criticality, which is an essential factor for informed decision-making in management (Doumpos et al., 2023; Makhov et al., 2025).

Previously, the study focused on technological and personnel risks, identifying key dependencies and proposing methods for their assessment. The next stage will involve a more detailed examination of organizational, compliance, and external risks. This will enable the development of a comprehensive management system that addresses the full range of operational risks, thereby increasing trust in automated risk management systems (European Central Bank, 2017; Chumakova et al., 2024b).

Technological risks play a critical role in the banking sector, where IT infrastructure failures can disrupt essential business processes. In 2023, Russian banks reported a 20% increase in cyberattacks compared to the previous year. The challenge is aggravated by the inefficiency of traditional methods for assessing and managing these risks in the context of digitalization and increasing data complexity. For example, regression analysis used to determine the relationship between risk factors and target indicators and clustering methods, which group data by similar features, fall short when addressing the nonlinear and multidimensional dependencies typical of operational risks (Chernobai et al., 2021; Chumakova et al., 2023b; Taratorin & Prokudina, 2023).

A study involving major Russian banks identified critical correlations between employee competence levels and the likelihood of operational incidents. The analysis showed that staff with low qualifications caused 68% of all incidents. Improving employee qualifications reduced the likelihood of errors by 34%, while disciplinary violations increased it by 45%. These findings highlight the importance of workforce management in mitigating operational risks (Makhov et al., 2023b).

Human errors and deliberate actions are the main drivers of personnel risks which are especially significant in credit institutions, where a single mistake can result in substantial losses. For example, one bank reported that an incorrectly executed transaction led to a loss equivalent to 2% of its annual profit (Chumakova et al., 2023a). This stipulates the necessity of adopting assessment and management methods capable of accounting for the human factor.

Managing operational risks requires modern tools capable of handling large datasets, accounting for nonlinear dependencies, and improving forecast accuracy (Makhov et al., 2023a). Developing and implementing methods, such as neural network ensembles and radial basis models, are essential steps toward enhancing business process resilience and reducing the likelihood of incidents.

MATERIALS AND METHODS

Real-world datasets from credit institutions were used for training and testing the models, incorporating parameters, such as incident criticality, impact on business processes, estimated financial losses, and incident frequency (Doumpos et al., 2023). These datasets were structured and normalized to optimize model performance (Makhov et al., 2023a). The data were divided into training (80%), validation, and testing subsets, ensuring even data distribution and preventing model overfitting (Seifipour & Mehrabian, 2025).

The neural network was optimized using methods like Adam and RMSprop implemented through the Keras library (Aguilera-Martos et al., 2023; Peer et al., 2021;). Data preprocessing techniques included normalization, which ensured stable model performance under varying input conditions.

As a result, the models demonstrated high accuracy and robustness in risk prediction, making them valuable for integration into operational risk management systems (Kaur et al., 2023).

Despite their strong performance, one of the main challenges of neural network models remains their "black box" nature, i.e., the difficulty in interpreting the results they produce (Chumakova et al., 2024a).

RESULTS AND DISCUSSION

It is important to assess the operational risks of credit institutions because it protects financial stability. Operational risks can generate significant losses, affecting results and the institutions' ability to meet their obligations. It also strengthens reputation, as operational errors or incidents can damage the institution's image and erode the trust of customers and stakeholders. It complies with regulations, as financial institutions are subject to regulations that require effective management of operational risks.

It optimizes operational efficiency, because it helps identify and mitigate operational risks, improving process efficiency and reducing costs.

The steps for assessing operational risks include:

1. Risk identification: The different types of operational risks that could affect the institution must be identified, considering its processes, systems, personnel, and environment.

2. Risk analysis: The probability and impact of each identified risk are assessed, using tools such as sensitivity analysis, stress testing, and statistical models.

3. Risk assessment: The risk level of each threat is determined, considering the combination of probability and impact.

4. Risk Mitigation: Measures are implemented to reduce the probability or impact of risks, such as process improvement, staff training, implementation of security systems, and diversification of operations.

5. Monitoring and Control: Monitoring and control systems are implemented to identify potential risk events and ensure that mitigation measures are effective.

Tools for assessing operational risks include:

Sensitivity analysis, which evaluates how changes in different variables could affect results; stress testing, which simulates risk scenarios to assess the institution's resilience.

Statistical Models use historical data and mathematical models to predict the probability of events occurring. Key Risk Indicators (KRIs), which also allow monitoring of the factors that drive operational risk, are also used.

Assessing operational risks is a continuous and fundamental process for the management of any financial and credit institution. By identifying, analyzing, and mitigating these risks, institutions can protect their financial stability, strengthen their reputation, comply with regulations, and optimize their operational efficiency.

Radial basis function networks (RBFNs) and deep neural networks (DNNs) have demonstrated high effectiveness in predicting critical operational risks. This section presents the results of prior research that laid the foundation of the proposed methods and identified limitations requiring further development and the application of emerging technologies, including XAI (Seifipour & Mehrabian, 2025).

One of the most effective research directions involved the application of RBFNs for assessing operational and IT risks. In a specific study, datasets comprising 21,600 operational risks classified by their criticality levels were utilized. The model was trained using the K-means clustering method to initialize the centers of radial functions, which enabled the achievement of high predictive accuracy.

The best results were achieved with a model containing 22 neurons in the hidden layer, which reached an accuracy of 97-98% on the test set after 1,000 training epochs (Seifipour & Mehrabian, 2025). This architecture effectively classified incidents caused by employee errors and IT failures. A key advantage of RBFNs is their ability to accurately assess risks with relatively small datasets, making them particularly suitable for use in environments with high variability in business processes (Kaur et al., 2023).

Alongside RBFNs, significant results were achieved with DNNs. These networks were used to predict the criticality of operational risks. On a dataset containing information about failures and personnel actions, DNNs achieved up to 99% accuracy in prediction tasks (Chumakova et al., 2024a).

DNNs with architectures like 10-25-25-3 demonstrated high forecasting performance when using the tanh activation function. This approach demonstrated the best results compared to other activation functions, such as sigmoid, and provided more stable outcomes (LeCun et al., 2015). These networks proved particularly useful for forecasting personnel risks, helping to identify critical employee errors and predict their potential impact on business processes (Kaplan & Mickelsen, 2014; Makhov et al., 2023a).

Moving from the review of previous studies, it can be concluded that existing neural network models, such as RBFNs and DNNs, have demonstrated high accuracy in assessing operational risks (Kaplan & Mickelsen, 2014). Despite these achievements, several unresolved issues require further investigation and new approaches. In particular, the need to enhance the interpretability of models using XAI remains a key aspect for their widespread application in financial organizations. XAI application will make models more transparent and increase trust in the decisions made, especially when evaluating the criticality of incidents that can significantly impact business processes.

Based on the results of previous studies and identified shortcomings, there is a need to develop more comprehensive solutions that combine the advantages of neural network models with new approaches focused on the explain ability of results.

The primary objective of this study is the development and experimental validation of new instrumental methods for assessing the criticality of operational risks, based on neural network ensembles and XAI (Chumakova et al., 2024b). These methods aim to improve the accuracy of predictions, enhance the model's resilience to data changes, and ensure the interpretability of results, which is crucial for their application in financial institutions, where decisions must be based on substantiated and transparent data (LeCun et al., 2015).

The study addresses the following key tasks:

1. Developing neural network ensemble architectures for assessing the criticality of operational risks;

2. Testing the developed models on real data from credit institutions;

3. Implementing XAI for explaining model results, including LIME, SHAP, and Grad-CAM;

4. Testing solutions in real business processes to assess their applicability and refining the models based on feedback.

To improve the accuracy of operational risk forecasts, an attempt was made to develop a neural network ensemble architecture that includes different types of neural networks, such as RBFNs and DNNs. Ensembles combine the strengths of each network. Specifically, RBFNs excel at classification tasks and are resistant to noise, while DNNs are good at handling nonlinear dependencies and large datasets (LeCun et al., 2015).

Each network in the ensemble has a unique configuration:

The RBFN consists of a single hidden layer with radial basis functions, where the activation function is responsible for calculating distances to the cluster centers;

The DNN includes several hidden layers with activation functions, such as ReLU or tanh, enabling the models to effectively process complex multidimensional dependencies in the data.

Modern tools and libraries, such as Keras and Python, are utilized for model development, providing flexibility and scalability in the design and testing phases. Keras enables the rapid prototyping and training of neural networks using various optimizers, such as Adam and RMSprop, which facilitate high prediction accuracy (Seifipour & Mehrabian, 2025).

Special attention is given to the method of combining the results of neural networks within the ensemble. Potential approaches include weighted voting, where each network is assigned, a weight based on its accuracy on the test dataset, or meta-algorithms like boosting to enhance the predictive power of the ensembles.

Model explainability is a crucial aspect of this research as financial organizations require transparent and justifiable predictions. To achieve this, XAI methods are applied, including:

LIME (Local Interpretable Model-Agnostic Explanations): this technique interprets model decisions by creating local linear models that explain specific predictions. It helps identify which parameters had the most significant influence on the result in each case (Chumakova et al., 2024b).

SHAP (SHapley Additive exPlanations): based on the game theory, SHAP calculates the contribution of each input parameter to the model's final prediction. This approach enhances model transparency and helps explain why a particular outcome was selected (Makhov et al., 2023a).

Grad-CAM (Gradient-Weighted Class Activation Mapping): this visualization method is applied to analyze data related to system failures and personnel actions. It generates heat maps that highlight which data regions had the most significant impact on the model's decisions (Makhov et al., 2023b).

Integrating these methods enables risk specialists to receive accurate predictions and understand the factors influencing the assessment of risk criticality. This is crucial for making informed management decisions (Chumakova et al., 2024a).

The real data collected from credit organizations is used for training and testing the developed models. These data include the following information:

Incidents involving IT systems;

Employee mistakes;

Financial losses caused by operational risks;

The criticality of incidents and their impact on business processes.

The data undergo meticulous preparation for model training, involving several key steps:

Data normalization: This step ensures that all parameters are scaled uniformly, allowing the models to train more effectively and avoiding the dominance of parameters with large value ranges;

Dataset splitting: The data are divided into training, validation, and testing subsets. This division ensures that the models are trained on one portion, validated on another, and tested on a separate set, providing an objective assessment of prediction accuracy.

Furthermore, mathematical methods, such as the Grubbs' test and the three-sigma rule, are used to assess the quality of datasets, helping to identify outliers and anomalies in the data. A correlation analysis of parameters is conducted using Spearman's rank correlation coefficient to exclude variables that do not influence the outcome and may complicate the model training process.

Thus, this study combines the development of highly accurate models with the implementation of advanced XAI methods, ensuring precise predictions and transparency necessary for effective operational risk management.

Despite the expected positive outcomes, the methods and models developed within this research have limitations that need to be considered when evaluating their applicability and potential for future development.

To achieve high accuracy and robustness, additional experiments with larger and more diverse datasets are required. The planned use of a limited dataset from credit institutions may restrict the generalizability of the models. In the future, expanding the database will be crucial to improving prediction quality, especially for rare and critical events.

The models to be developed are focused on operational risks in credit institutions. To apply them in other industries (manufacturing, transportation, healthcare), adaptation will be required. It will be important to conduct further research to assess how applicable these methods are beyond the financial sector and how they can be tailored to the specific needs of each industry.

These limitations will be considered when planning the subsequent phases of the project to ensure the continued development and improvement of the proposed models and methods.

CONCLUSIONS

The research focuses on developing methods for assessing the criticality of operational risks using neural network ensembles and XAI. The study analyzed RBFNs and DNNs, which demonstrated strong performance in classifying and forecasting incidents in credit institutions. Implementing XAI will enhance trust in the decisions made by these models and improve their application in real business processes. Future plans include expanding experiments with larger datasets and adapting the models for other industries.

Applying LIME, SHAP, and Grad-CAM is a key step toward increasing trust in the models and ensuring their usability in business. This is particularly critical in financial organizations, where errors can result in substantial financial losses.

The study acknowledges limitations related to the need for larger datasets and the adaptation of models for other sectors. These factors have been accounted for in the planning of future research stages.

Thus, the methods and technologies developed in this research have the potential to significantly enhance operational risk management processes. They offer high predictive accuracy and transparency, enabling organizations to minimize risks and optimize business processes in the context of high uncertainty and data complexity.

This research was conducted as part of a state assignment in the field of scientific activity by the Ministry of Science and Higher Education of the Russian Federation. The project “Models, Methods and Algorithms of Artificial Intelligence in Economic Applications for Multidimensional Data Analysis and Stylization, Time Series Forecasting, and Recommender System Design” is registered under project No. FSSW-2023-0004.

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