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Investigating the Drivers of Operational Risk in the Central Branches of the Selected Banks in Tehran and Strategies for Its Mitigation

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A B S T R A C T

The main objective of the present study was to investigate the drivers of operational risk in the central branches of the selected banks in Tehran and to identify strategies for reducing such risks. In the present study, the statistical population consisted of all experts, specialists, and officials working in the headquarters and branches of the selected banks in Tehran. A random sampling method was employed in this research. To determine content validity and assess whether the data collection instrument adequately represented the content intended to be measured, 10 questionnaires were distributed among experts. Based on the collected information and considering the Content Validity Ratio (CVR) according to Lawshe's table, the minimum acceptable validity level, given the number of evaluators, was determined to be 62%. Furthermore, Cronbach's alpha coefficient and composite reliability were used to examine the reliability of the questionnaire. Since the Average Variance Extracted (AVE) for all variables exceeded 0.50, and the composite reliability and Cronbach's alpha values for all variables were greater than 0.70, the measurement instrument (questionnaire) was considered valid and reliable. Four major tools for data collection include documents and records, observation, interviews, and questionnaires. In this study, valuable information was gathered through interviews with 15 managers and experts. After several stages of preliminary reviews and modifications, the final questionnaire consisting of 35 items was prepared for implementation. Descriptive and inferential statistics were used to analyze the research data. Descriptive statistics were employed to calculate measures of central tendency and dispersion, while inferential statistics were used to test the research hypotheses. Data analyses were conducted using SPSS, VisualPLS, and MINITAB software packages. Based on the findings, the significant impact of human resource weaknesses, as a driver of operational risk, on the occurrence of losses related to operational risk in the selected banks was confirmed. In addition, the substantial impact of process weaknesses, as a driver of operational risk, on the occurrence of operational risk losses in the selected banks was also confirmed. The findings further indicated that external events had a significant effect, as a driver of operational risk, on the occurrence of operational risk losses in the banking sector.

Keywords: *Operational risk, human resource weaknesses, process weaknesses, external events, system weaknesses.*

1. Introduction

Deep learning has emerged as one of the most transformative technologies in contemporary computational science, enabling machines to learn complex patterns from large-scale data and perform predictive tasks with remarkable precision. Unlike traditional machine learning methods that often rely on handcrafted features and shallow architectures, deep learning models utilize multi-layer neural structures capable of automatically extracting hierarchical representations from raw data. This capability has significantly expanded the application of artificial intelligence across diverse domains including healthcare, finance, agriculture, engineering, social media analysis, transportation systems, and cybersecurity (Ahmed et al., 2023; Zheng et al., 2023). The increasing availability of large datasets, advances in computational power, and the development of sophisticated neural network architectures have accelerated the adoption of deep learning models for solving highly complex analytical problems that conventional methods struggle to address (Chen et al., 2024; Wu, 2024).

One of the most significant strengths of deep learning lies in its ability to model nonlinear relationships and uncover latent structures within high-dimensional data. Traditional statistical methods often fail to capture intricate dependencies among variables, particularly when dealing with temporal, spatial, or relational information. Deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Graph Neural Networks (GNNs) have provided robust solutions for learning from complex data structures (Pham et al., 2022; Ramaswamy & Jayakumar, 2023). These models have demonstrated substantial improvements in classification, prediction, segmentation, anomaly detection, and feature extraction tasks across numerous scientific and industrial applications (Ali et al., 2024; He et al., 2025). The adaptability of deep learning models enables them to process heterogeneous data formats including images, text, signals, graphs, and sequential observations, thereby broadening their practical utility.

In the healthcare domain, deep learning has revolutionized disease diagnosis, medical imaging analysis, and physiological signal interpretation. Recent studies have shown that deep neural architectures can outperform conventional approaches in detecting and classifying complex medical conditions from imaging and sensor-based datasets. For example, deep learning models have been effectively employed in electrocardiogram analysis for cardiovascular disease prediction and heartbeat characterization, achieving high accuracy and improved diagnostic reliability (He et al., 2025; Wu, 2024). Similarly, deep learning techniques have shown remarkable effectiveness in identifying neurological and psychiatric disorders from magnetic resonance imaging data, enabling automated diagnostic assistance in clinical environments (Zhang et al., 2021). In cancer diagnosis, hybrid CNN-LSTM architectures and ensemble learning methods have demonstrated substantial capability in breast cancer detection, tumor segmentation, and thermographic image classification (Begum et al., 2022; Munguía-Siu et al., 2024; Ranjbarzadeh et al., 2023; Selvarani & Jose, 2023). These findings indicate that deep learning models can learn highly discriminative medical features while reducing dependency on manual interpretation.

Another important area where deep learning has achieved considerable progress is neuroscience and biomedical signal processing. Electroencephalogram-based emotion recognition and stress detection systems have increasingly relied on deep neural networks due to their capacity to extract meaningful temporal and spectral patterns from noisy biological signals (Roy et al., 2023; J. Wang et al., 2023). Hybrid deep learning frameworks integrating CNNs, RNNs, and attention mechanisms have improved the detection of emotional states, stress responses, and neurological abnormalities by effectively modeling temporal dependencies and nonlinear signal characteristics (Kumar, 2023; Roy et al., 2023). Furthermore, deep learning methods have also advanced seizure detection from intracranial EEG recordings, contributing to more reliable clinical monitoring systems and personalized neurological treatment strategies (Qamar, 2025). The integration of attention mechanisms and recurrent architectures has further enhanced the interpretability and predictive stability of these biomedical systems.

Beyond healthcare, deep learning has become a central technology in financial forecasting and economic prediction. Financial markets produce highly nonlinear and dynamic time-series data that challenge traditional econometric approaches. Deep learning architectures have shown strong predictive capabilities in modeling stock prices, market volatility, and economic indicators due to their ability to learn hidden temporal dependencies and complex feature interactions (Chen et al., 2024; Liu et al., 2022). Hybrid models integrating CNNs, LSTMs, and attention layers have demonstrated improved forecasting accuracy compared with conventional machine learning techniques, especially in environments characterized by noise and uncertainty (Chen et al., 2024). Furthermore, deep learning has increasingly been integrated into broader economic analysis, where neural architectures are used for predictive analytics, optimization, and decision-making support (Zheng et al., 2023). The growing reliance on AI-driven financial systems highlights the need for scalable and interpretable predictive models capable of handling real-time data streams.

The rapid growth of social media platforms and digital communication systems has also encouraged the application of deep learning for sentiment analysis, opinion mining, and behavioral prediction. Textual data generated on social networks are often unstructured, context-dependent, and emotionally nuanced, making traditional text analysis techniques insufficient. Deep learning models, particularly CNNs and LSTMs, have substantially improved sentiment classification by capturing semantic and contextual relationships within textual sequences (Chaudhary et al., 2024; Ramaswamy & Jayakumar, 2023). Twitter sentiment analysis, customer satisfaction classification, and emotional recognition systems increasingly rely on deep learning architectures due to their ability to process large-scale linguistic datasets with high accuracy (Aftan & Shah, 2023; Chaudhary et al., 2024). Ensemble learning methods combining recurrent and convolutional structures have further enhanced sentiment detection performance by integrating contextual and sequential representations of language (Ramaswamy & Jayakumar, 2023). These developments illustrate the transformative role of deep learning in computational social science and digital communication analysis.

Deep learning has additionally transformed agricultural analytics and environmental forecasting. Agricultural systems involve highly dynamic interactions among weather conditions, soil properties, crop characteristics, and environmental factors, requiring predictive models capable of handling nonlinear multivariate relationships. Machine learning and deep learning approaches have demonstrated substantial effectiveness in crop yield prediction, resource management, and sustainable agricultural planning (Jabed & Murad, 2024). Deep learning architectures can integrate heterogeneous agricultural datasets and generate accurate predictive insights that support food security and precision farming initiatives. Similarly, geological hazard forecasting has benefited from deep learning applications capable of analyzing spatial-temporal environmental data and identifying risk patterns associated with natural disasters (X. Wang et al., 2023). These advancements demonstrate the growing importance of AI-driven predictive systems in sustainability and environmental management.

Cybersecurity and intrusion detection systems represent another critical area where deep learning has gained significant attention. Modern cyberattacks are increasingly sophisticated, adaptive, and difficult to detect using rule-based or traditional statistical approaches. Deep learning-based intrusion detection systems have shown superior performance in recognizing anomalous patterns and malicious activities within large-scale network traffic data (Al-Haija & Droos, 2024; Sadia et al., 2024; Salih et al., 2021). Advanced neural architectures can automatically extract complex behavioral signatures from network traffic and dynamically adapt to evolving threats, improving detection accuracy and reducing false alarm rates (Al-Haija & Droos, 2024). In wireless sensor networks and Internet of Things environments, machine learning and deep learning approaches have become essential for protecting distributed systems from intrusion attempts and unauthorized access (Sadia et al., 2024). The integration of attention mechanisms and hybrid learning frameworks has further enhanced the robustness and scalability of these cybersecurity solutions.

The emergence of graph-based deep learning has expanded the applicability of artificial intelligence to relational and non-Euclidean data structures. Traditional deep learning models are generally designed for grid-like data representations such as images or sequences, making them less suitable for graph-structured datasets characterized by irregular topologies and complex interdependencies. Graph Neural Networks and related graph-based architectures have addressed this limitation by enabling neural computation directly on graph structures (Li & Hsu, 2022). These models aggregate information from neighboring nodes and learn relational representations that capture both structural and semantic characteristics of networks. Applications of graph-based deep learning now span social networks, recommendation systems, biological interaction networks, urban infrastructure analysis, and financial transaction systems (Kwon & Kim, 2021; Zhang et al., 2023).

In urban and infrastructural systems, machine learning models have increasingly been integrated into drainage systems, smart cities, and structural monitoring frameworks. Urban drainage systems generate highly interconnected spatial and hydrological data that require advanced predictive analysis for flood management and infrastructure optimization. Machine learning and deep learning methods have demonstrated significant effectiveness in predicting drainage system behavior and improving urban water management strategies (Kwon & Kim, 2021). Similarly, structural health monitoring systems increasingly rely on artificial neural networks and deep learning algorithms to detect anomalies, predict failures, and assess infrastructure integrity in real time (Atia et al., 2024). These technologies enable continuous monitoring of engineering systems while reducing maintenance costs and improving operational safety.

Deep learning has also demonstrated substantial potential in multimodal learning and action recognition systems. Video-based human action recognition represents a challenging problem due to temporal dependencies, spatial complexity, and contextual variability within video sequences. Deep learning frameworks combining CNNs and recurrent architectures have significantly improved action recognition accuracy by simultaneously modeling spatial and temporal information (Pham et al., 2022). Multimodal deep learning systems integrating audio, visual, textual, and sensor data have further expanded the capability of AI systems to understand human behavior, emotional states, and contextual interactions (Kumar, 2023). These approaches reflect the broader trend toward integrating heterogeneous information sources within unified predictive frameworks.

Despite the impressive advancements of deep learning technologies, several challenges continue to limit their widespread deployment and reliability. One major issue concerns the requirement for large-scale labeled datasets, which are often expensive and time-consuming to obtain. Many deep learning models also suffer from high computational complexity and substantial energy consumption during training and inference processes (Ahmed et al., 2023). Another critical limitation involves interpretability and explainability, as many deep neural networks function as black-box systems whose internal decision-making processes remain difficult to understand (Zheng et al., 2023). This issue becomes particularly problematic in high-stakes domains such as healthcare, finance, and cybersecurity, where transparency and trustworthiness are essential. Furthermore, overfitting, data imbalance, model bias, and adversarial vulnerability remain persistent concerns in deep learning research (Ljubic et al., 2022).

Researchers have increasingly focused on developing hybrid and ensemble learning approaches to overcome these limitations and improve predictive robustness. Hybrid models combining CNNs, RNNs, LSTMs, graph-based architectures, and attention mechanisms have demonstrated enhanced generalization performance across multiple domains (Begum et al., 2022; Munguía-Siu et al., 2024; Ramaswamy & Jayakumar, 2023). Ensemble learning frameworks can integrate complementary strengths of multiple architectures while reducing predictive uncertainty and improving classification stability. Moreover, advances in transfer learning, self-supervised learning, and federated learning are creating new opportunities for improving model scalability and reducing dependence on labeled datasets (Ahmed et al., 2023). These emerging developments indicate that deep learning continues to evolve toward more adaptive, interpretable, and efficient predictive systems.

Overall, the existing literature demonstrates that deep learning has become a foundational technology for predictive analysis, feature extraction, classification, and intelligent decision-making across numerous scientific and industrial domains. From healthcare diagnostics and biomedical signal processing to financial forecasting, cybersecurity, agriculture, urban infrastructure, and social media analytics, deep learning models have consistently demonstrated superior performance compared with traditional analytical approaches (Chaudhary et al., 2024; Chen et al., 2024; Jabed & Murad, 2024; Wu, 2024). Nevertheless, challenges related to interpretability, scalability, computational cost, and robustness continue to motivate further research into advanced neural architectures and hybrid learning systems (Ahmed et al., 2023; Zheng et al., 2023). Therefore, the aim of this study is to investigate the application of deep learning techniques for predictive analysis and classification tasks by examining their effectiveness, challenges, and practical implications across complex data-driven environments.

2. Methods and Materials

The present study was applied in terms of purpose, as its findings can be practically utilized not only by the selected banks to identify the factors affecting operational risk, but also by other similar financial institutions seeking to improve operational risk management practices. In terms of research design, the study adopted a descriptive-survey approach. Since the primary objective of the research was to identify the factors influencing operational risk in the Iranian banking system and the required data were collected from a target sample using a questionnaire, the study was categorized as survey research in terms of data collection methodology. The study was conducted in Tehran, Iran, and the data were collected cross-sectionally during March 2025.

The statistical population consisted of all experts, specialists, managers, and officials working in the headquarters and branches of the selected banks in Tehran. A random sampling method proportional to the population size of each bank was employed in the study. This approach was considered appropriate because the research population was heterogeneous and included different organizational groups with varying population proportions. In proportional stratified random sampling, the total sample size was multiplied by the proportion of specialists in each bank in order to determine the quota assigned to each institution. Subsequently, participants within each bank were selected randomly. The final sample included employees and experts from several major Iranian banks, including Bank Melli, Bank Maskan, Bank Saderat, Bank Tejarat, and Parsian Bank. A total of 196 participants were included in the quantitative phase of the study.

Data collection in this study was conducted using documentary review, interviews, and questionnaires. Initially, a comprehensive review of books, academic articles, banking reports, and online resources related to operational risk management was undertaken in order to establish the theoretical foundations of the study and identify the principal dimensions of operational risk drivers. In addition, the guidelines and recommendations issued by the Central Bank of Iran regarding operational risk management were reviewed and incorporated into the development of the research instrument.

Qualitative data were also gathered through semi-structured interviews with 15 managers and experts specializing in operational risk management within the banking sector. The interviews provided valuable insights into the practical dimensions of operational risk and contributed to the identification of key indicators related to human resource weaknesses, process deficiencies, external events, and system-related issues. Based on the literature review, expert opinions, and interview findings, the initial questionnaire was designed under the supervision of academic advisors and specialists in operational risk management.

To ensure the validity of the instrument, content validity and face validity were assessed. For this purpose, 10 questionnaires were distributed among experts to evaluate whether the items adequately represented the intended constructs. The Content Validity Ratio (CVR) was calculated according to Lawshe's method, and considering the number of evaluators, the minimum acceptable threshold was determined to be 0.62. The questionnaire items met the required validity criteria, and revisions were made based on expert feedback to improve clarity, comprehensibility, and relevance. A pilot assessment was also conducted using a small sample in order to identify possible ambiguities and weaknesses in the wording of the items. After several stages of revision and refinement, the final questionnaire consisting of 35 items was prepared for implementation. In addition to the main research variables, four demographic questions were included to collect participants' individual and organizational characteristics.

The reliability and construct validity of the questionnaire were assessed using Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE). The Cronbach's alpha coefficients for all latent variables exceeded 0.70, indicating satisfactory internal consistency among the questionnaire indicators. Similarly, the composite reliability values for all constructs were greater than 0.60, confirming acceptable reliability of the measurement model. Furthermore, the AVE values for all variables exceeded 0.50, indicating adequate convergent validity. The results demonstrated that the measurement instrument possessed appropriate levels of validity and reliability for assessing the operational risk drivers under investigation.

The collected data were analyzed using both descriptive and inferential statistical methods. Descriptive statistics were employed to calculate measures of central tendency and dispersion, including means and standard deviations, in order to summarize the characteristics of the research variables and respondents. Inferential statistical techniques were then utilized to test the research hypotheses and examine the relationships between operational risk drivers and operational risk losses within the selected banks.

The statistical analyses were conducted using SPSS, VisualPLS, and MINITAB software packages. Structural equation modeling and related analytical procedures were applied to evaluate the proposed conceptual framework and examine the significance of the relationships among variables. The decision-making process regarding hypothesis testing was based on the significance levels generated by the statistical software. Hypotheses were considered statistically significant when the calculated significance level was equal to or less than 0.05. In such cases, the null hypothesis was rejected and the alternative hypothesis was accepted. Conversely, if the significance level exceeded 0.05, the null hypothesis was retained. In addition, the calculated test statistics for each analysis were compared with their corresponding critical values to further determine the acceptance or rejection of the hypotheses. Through these procedures, the study systematically evaluated the effects of human resource weaknesses, process deficiencies, external events, and system weaknesses on operational risk within the selected banks in Tehran.

3. Findings and Results

The demographic profile of the respondents was examined based on gender, age, educational level, and work experience. The sample consisted of 196 banking experts, managers, and specialists. Gender distribution was controlled equally, with women and men each representing 50.0% of the sample. In terms of age, most respondents were between 30 and 40 years old, indicating that the sample was relatively young. Regarding education, most participants held a bachelor's degree, while a smaller proportion had master's or doctoral degrees. In terms of work experience, the largest group consisted of respondents with more than 10 years of professional experience.

Table 1

Frequency and Percentage Distribution of Demographic Characteristics

Characteristic	Subgroup	Frequency	Percentage	Mode
Gender	Female	98	50.0	Bimodal
	Male	98	50.0	
Age	Less than 30 years	52	26.5	30–40 years
	30–40 years	117	59.7	
	More than 40 years	27	13.8	
Education	Bachelor's degree	166	84.7	Bachelor's degree
	Master's degree and PhD	30	15.3	
Work experience	Less than 6 years	53	27.0	More than 10 years
	6–10 years	57	29.1	
	More than 10 years	86	43.9	

In addition to demographic variables, 35 indicators were used to measure the variables of the conceptual model. These indicators assessed four drivers of operational risk in banks: human resources, processes, external events, and systems. Responses were measured on a five-point continuum ranging from "very low" to "very high." The human resource driver was measured by eight items. The median and mode of four items were "high," three items were "moderate," and one item was "low," indicating that human resource weaknesses generally had an above-average role in creating operational risk. The process driver was measured by 13 items. The median and mode of one item were "very high," five items were "high," four items were "moderate," and three items were "low," showing that process weaknesses also had an above-average role in operational risk. The external event driver was measured by four items, with one item classified as "very high," one as "high," one as "moderate," and one as "low," suggesting an above-average overall effect. The system driver was measured by 10 items; four items were classified as "high," one as "moderate," and five as "low," indicating a moderate overall role in operational risk.

Table 2

Summary of Response Patterns for Operational Risk Drivers

Operational Risk Driver	Number of Items	Dominant Response Pattern	Overall Interpretation
Human resource weaknesses	8	Four high, three moderate, one low	Above-average effect on operational risk
Process weaknesses	13	One very high, five high, four moderate, three low	Above-average effect on operational risk
External events	4	One very high, one high, one moderate, one low	Above-average effect on operational risk
System weaknesses	10	Four high, one moderate, five low	Moderate effect on operational risk

To extract the main research variables from the raw data, the mean score of the items related to each construct was calculated. Descriptive indices of central tendency and dispersion were then used to evaluate the four research variables. The mean score of the human resource driver was 3.434, with a standard deviation of 0.385 and variance of

0.148. Since its mean was higher than the theoretical mean of 3.00, human resource weaknesses were evaluated as having a strong role in creating operational risk. The variable showed positive skewness and negative kurtosis. The skewness deviation coefficient exceeded the absolute value of 1.96, indicating deviation from normality in terms of skewness, while the kurtosis deviation coefficient did not exceed the critical value.

The mean score of the process driver was 3.194, with a standard deviation of 0.331 and variance of 0.109. This mean was also higher than 3.00, indicating a considerable role for process weaknesses in operational risk. The variable had negative skewness and negative kurtosis. The skewness deviation coefficient was lower than the absolute critical value of 1.96, while the kurtosis deviation coefficient exceeded the critical value, indicating deviation from normality in terms of kurtosis. The mean score of external events was 3.274, with a standard deviation of 0.471 and variance of 0.222. This result confirmed the strong role of external events in operational risk. The variable had negative skewness and positive kurtosis. The mean score of the system driver was 3.007, with a standard deviation of 0.414 and variance of 0.172. Since this mean was almost equal to 3.00, system weaknesses were evaluated as having a moderate role in operational risk.

Table 3

Descriptive Statistics of the Research Variables

Variable	N	Mean	Standard Deviation	Variance	Skewness	Kurtosis	Skewness Deviation	Kurtosis Deviation
Human resource driver	196	3.434	0.385	0.148	0.355	-0.484	2.042	-1.400
Process driver	196	3.194	0.331	0.109	-0.065	-0.845	-0.376	-2.445
External event driver	196	3.274	0.471	0.222	-0.549	0.075	-3.164	0.218
System driver	196	3.007	0.414	0.172	-0.643	0.579	-3.701	1.676

Before testing the research hypotheses, the normality of the distribution of the variables was examined using the Kolmogorov–Smirnov test. Since the data were collected from 196 experts and the objective was to compare the empirical mean of each variable with the theoretical mean of the measurement scale, a mean comparison approach was initially considered. However, the results indicated that the distributions of the research variables were not normal. Therefore, the nonparametric one-sample Runs test was used to test the research hypotheses.

Table 4

Kolmogorov–Smirnov Test Results for the Distribution of Research Variables

Variable	N	Z Statistic	Significance Level	Result
Human resource driver	196	3.42	0.000	Not normally distributed
Process driver	196	6.83	0.000	Not normally distributed
External event driver	196	5.087	0.000	Not normally distributed
System driver	196	1.073	0.411	Distribution assumption not confirmed for hypothesis testing

The first hypothesis examined whether human resource weaknesses affected operational risk. The results of the one-sample Runs test showed that the calculated Z statistic was 3.421, which was greater than the critical value of 1.96. Moreover, the significance level was 0.000, which was lower than 0.05. Therefore, the null hypothesis was rejected at the 95% confidence level, and the alternative hypothesis was supported. Accordingly, from the perspective of branch managers and experts, human resource weaknesses are among the factors affecting operational risk.

The second hypothesis examined whether process weaknesses affected operational risk. The calculated Z statistic was 6.835, which exceeded the critical value of 1.96, and the significance level was 0.000. Therefore, the null hypothesis was rejected, and the second hypothesis was confirmed. This finding indicates that process weaknesses are among the factors influencing operational risk in the selected banks.

The third hypothesis examined whether external events affected operational risk. The calculated Z statistic was 5.087, which was greater than 1.96, and the significance level was 0.000. Therefore, the null hypothesis was rejected, and the third hypothesis was supported. This result shows that external events are significant drivers of operational risk from the perspective of the respondents.

The fourth hypothesis examined whether system weaknesses affected operational risk. The calculated Z statistic was 1.073, which was lower than the critical value of 1.96, and the significance level was 0.164, which was higher than 0.05. Therefore, the null hypothesis was not rejected, and the fourth hypothesis was not confirmed. This means that system weaknesses were not identified as a statistically significant factor affecting operational risk in the selected banks.

Table 5

Results of Hypothesis Testing Using the One-Sample Runs Test

Hypothesis	Variable	Test Value	N	Number of Runs	Z Statistic	Significance Level	Result
First hypothesis	Human resource weaknesses	3.00	196	100	3.421	0.000	Confirmed
Second hypothesis	Process weaknesses	3.00	196	100	6.835	0.000	Confirmed
Third hypothesis	External events	3.00	196	100	5.087	0.000	Confirmed
Fourth hypothesis	System weaknesses	3.00	196	100	1.073	0.164	Not confirmed

4. Discussion and Conclusion

The present study investigated the drivers of operational risk in the central branches of selected banks in Tehran and examined the role of four major factors, including human resource weaknesses, process weaknesses, external events, and system weaknesses, in creating operational risk. The findings demonstrated that human resource weaknesses, process weaknesses, and external events had significant positive effects on operational risk, whereas system weaknesses did not show a statistically significant effect. Overall, the results indicate that operational risk in the banking sector is shaped more strongly by managerial, procedural, and environmental factors than by technological system deficiencies alone. These findings contribute to the growing literature on banking operational risk management and provide empirical evidence regarding the relative importance of different operational risk drivers within the Iranian banking context.

One of the most important findings of the study was the significant effect of human resource weaknesses on operational risk. The descriptive findings showed that the mean value of the human resource driver exceeded the theoretical average, indicating that respondents perceived employee-related weaknesses as a substantial source of operational risk. Furthermore, the hypothesis testing results confirmed that human resource deficiencies significantly contributed to operational risk occurrence in the selected banks. This finding can be explained by the fact that banking operations rely heavily on the performance, competence, integrity, and coordination of employees and managers. Human errors in transaction processing, customer service, data recording, compliance implementation, and decision-making may directly result in financial losses, reputational damage, and operational disruptions. In many cases, operational failures originate not from technical defects but from insufficient employee training, lack of accountability, weak supervision, low motivation, or failure to follow standardized procedures.

The findings related to human resource weaknesses are consistent with the results reported by (Shoja et al., 2021), who emphasized the multidimensional nature of human resource operational risk and highlighted the importance of employee competence, organizational behavior, and managerial supervision in reducing operational risk exposure. The results are also aligned with the study conducted by (Mohammadi Khanqah et al., 2025), which identified human-related organizational factors as central components of banking risk. Similarly, (Angouraj Taghavi, 2025) emphasized that internal auditing and employee monitoring mechanisms play a significant role in reducing operational risk by identifying weaknesses in staff performance and control implementation. These findings collectively indicate that operational risk management in banks cannot be achieved solely through technological investment or regulatory compliance; instead, it requires continuous investment in human capital development, professional ethics, performance evaluation, and organizational learning.

Another important finding of the present study was the significant effect of process weaknesses on operational risk. The results demonstrated that deficiencies in banking procedures, operational workflows, and internal processes were among the strongest predictors of operational risk. The process driver showed an above-average mean score, and the hypothesis test confirmed its statistically significant influence. This finding suggests that weak operational procedures, inadequate documentation, unclear responsibilities, ineffective monitoring systems, and inconsistencies in operational execution increase the probability of banking errors and losses. Because banking institutions depend on highly structured and sequential processes, any procedural weakness can spread rapidly across organizational operations and generate substantial operational disruptions.

The findings concerning process weaknesses are consistent with previous studies on operational risk management barriers and process vulnerabilities in banks. (Fallah Shams & Siahkarzadeh, 2019) reported that weak organizational processes and ineffective implementation of operational risk management frameworks constitute major barriers to risk reduction in Iranian banks. Likewise, (Sadeghi Amroabadi & Yazdani, 2020) emphasized the importance of identifying operational risks in information management, communication systems, and customer service processes within banking institutions. The current findings are also supported by (Mostafaei Dolatabad et al., 2018), who demonstrated that operational risks are interconnected and can be systematically analyzed through fuzzy cognitive mapping techniques. These studies collectively indicate that operational risk emerges not only from isolated failures but also from structural process deficiencies that weaken organizational reliability and internal control quality.

The significant role of external events in operational risk was another important outcome of the study. The results indicated that external events had a statistically significant effect on operational risk, and respondents evaluated this factor as having an above-average influence. External events may include macroeconomic instability, regulatory changes, cyber threats, political uncertainty, environmental disruptions, market volatility, or unexpected crises that negatively affect banking operations. Unlike internal factors, external events are often difficult to predict and control, which increases their potential to generate operational losses. In developing banking systems, where banks may face economic instability and technological vulnerabilities simultaneously, the impact of external events becomes even more severe.

The findings related to external events are consistent with the study conducted by (Abdymomunov et al., 2020), which demonstrated that operational losses in the banking sector are strongly associated with macroeconomic conditions. Similarly, (Liang et al., 2024) showed that broader economic growth targets and macroeconomic pressures affect bank risk exposure. These findings suggest that operational risk cannot be analyzed independently from the economic and environmental context in which banks operate. Furthermore, the results align with (Mohammadi, 2026), who emphasized the relationship between banking risks and the overall stability of the Iranian banking system. When external shocks occur, operational vulnerabilities within banks become more visible, and institutions with weaker risk management structures are more likely to experience significant operational disruptions.

In contrast to the previous findings, the present study found that system weaknesses did not have a statistically significant effect on operational risk. Although descriptive statistics indicated that system-related issues had a moderate influence, the hypothesis testing results showed that the effect was not statistically significant. This finding may indicate that the selected banks have already achieved relatively acceptable levels of technological infrastructure and system reliability, thereby reducing the direct impact of system weaknesses on operational risk. In recent years, many banks have invested heavily in digital banking platforms, cybersecurity systems, transaction monitoring technologies, and automated operational controls. As a result, technological systems may no longer constitute the primary source of operational risk compared with human or process-related deficiencies.

However, the absence of a significant relationship between system weaknesses and operational risk does not imply that technological systems are unimportant. Instead, it may suggest that banks have become more successful in controlling system-related risks relative to other dimensions of operational risk. This interpretation is partially consistent with studies emphasizing the growing role of advanced technologies and machine learning methods in operational risk identification and management (Gonzalez-Carrasco et al., 2019; Zhou et al., 2021). The use of artificial intelligence, automated classification systems, and digital monitoring tools may have strengthened operational resilience against purely technical failures. Moreover, (Naderi et al., 2025) demonstrated that machine learning algorithms can improve the prediction of operational risk occurrence, suggesting that technological advancement may actually reduce certain categories of operational risk when properly implemented.

The findings of the study also reinforce the importance of integrated governance and risk management mechanisms in the banking industry. Operational risk management requires coordination among internal controls, risk governance structures, internal auditing systems, process monitoring, employee supervision, and strategic management. Studies on corporate governance and banking risk have shown that governance quality significantly influences organizational risk-taking behavior and systemic stability (Addo et al., 2021; Bakhtiari & Yaghoobpour, 2024; Nosrati et al., 2025). Therefore, the operational risk drivers identified in the present study should not be viewed separately from the broader governance environment of banks. Weak governance mechanisms may intensify human and procedural weaknesses, while effective governance can strengthen organizational discipline and risk responsiveness.

Another implication of the findings concerns the role of operational risk databases and analytical methods in banking risk management. The identification of significant operational risk drivers highlights the necessity of collecting, classifying, and analyzing operational risk events systematically. (Shafiei et al., 2022) emphasized the role of operational risk event databases in improving banking risk management by enabling institutions to monitor patterns, estimate exposure, and implement preventive strategies. Likewise, studies using Bayesian networks, fuzzy models, and deep-learning techniques have demonstrated that operational risk can be predicted more effectively when organizations employ systematic data analysis tools (Ahmadi & Takloo, 2013; Pena et al., 2021). The current study supports these arguments by showing that operational risk drivers are measurable and analyzable through structured empirical methods.

The results of the study further support the argument that operational risk management should be treated as a strategic rather than purely technical function. Banking operational risk is deeply connected with organizational culture, employee behavior, governance quality, environmental uncertainty, and process effectiveness. This perspective is consistent with the findings of (Naderi & Rastegar, 2022), who emphasized the importance of integrating different operational risk management methodologies in the banking industry. Similarly, (Fadaei et al., 2021) highlighted the interconnected nature of risk factors and the importance of identifying causal relationships among them. Therefore, reducing operational risk requires a comprehensive organizational approach that integrates strategic planning, employee training, internal control, governance mechanisms, and technological support systems.

Overall, the findings of the present study indicate that operational risk in the selected banks is primarily driven by weaknesses in human resources, organizational processes, and external environmental conditions. These findings suggest that banks should prioritize organizational and managerial reforms in addition to technological investment. Strengthening employee competence, improving process standardization, increasing internal audit effectiveness, enhancing governance mechanisms, and preparing for environmental uncertainty can significantly reduce operational risk exposure. Furthermore, the study contributes to the operational risk literature by providing empirical evidence from the Iranian banking industry and clarifying the relative importance of different operational risk drivers within banking headquarters and branch environments.

One limitation of the present study was that the data were collected only from selected banks in Tehran, which may reduce the generalizability of the findings to other provinces, private financial institutions, or international banking environments. In addition, the study relied on self-reported questionnaire data collected from managers and experts, which may be influenced by subjective perceptions or response bias. The cross-sectional nature of the research also limited the ability to examine changes in operational risk drivers over time or under different economic conditions.

Future research is recommended to investigate operational risk drivers in a broader range of financial institutions, including private banks, digital banks, insurance companies, and non-banking financial organizations. Researchers may also apply longitudinal designs to examine how operational risk factors evolve during economic crises, technological transitions, or regulatory reforms. In addition, future studies could integrate qualitative methods, machine learning techniques, and operational risk databases to develop more predictive and dynamic models of operational risk management.

From a practical perspective, banking managers should prioritize the development of comprehensive employee training programs, strengthen process monitoring systems, and improve organizational internal controls in order to reduce operational risk exposure. Banks should also establish integrated operational risk databases, increase the effectiveness of internal auditing mechanisms, and adopt proactive risk management frameworks capable of responding to external environmental changes. Furthermore, policymakers and banking regulators should encourage the implementation of standardized operational risk management systems and support the development of advanced analytical tools for operational risk identification and prevention.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Abdymomunov, A., Curti, F., & Mihov, A. (2020). US Banking Sector Operational Losses and the Macroeconomic Environment. *Journal of Money, Credit and Banking*, *52*(1), 115-144. https://doi.org/10.1111/jmcb.12661

Addo, K. A., Hussain, N., & Iqbal, J. (2021). Corporate Governance and Banking Systemic Risk: A Test of the Bundling Hypothesis. *Journal of International Money and Finance*, *115*, 102327.

Aftan, S., & Shah, H. (2023). Using the AraBERT Model for Customer Satisfaction Classification of Telecom Sectors in Saudi Arabia. *Brain Sciences*, *13*(1), 147. https://doi.org/10.3390/brainsci13010147

Ahmadi, A., & Takloo, M. (2013). Operational Risk Modeling of Banks Using Bayesian Networks. First National Conference on Monetary and Banking Management Development, Tehran.

Ahmed, S. F., Alam, M. S. B., Hassan, M., Rozbu, M. R., Ishtiak, T., Rafa, N., Mofijur, M., Ali, A. B. M. S., & Gandomi, A. H. (2023). Deep Learning Modelling Techniques: Current Progress, Applications, Advantages, and Challenges. *Artificial Intelligence Review*, *56*(11), 13521-13617. https://doi.org/10.1007/s10462-023-10466-8

Al-Haija, Q. A., & Droos, A. (2024). A Comprehensive Survey on Deep Learning-based Intrusion Detection Systems in Internet of Things (<scp>IoT</Scp>). *Expert Systems*, *42*(2). https://doi.org/10.1111/exsy.13726

Ali, M., Shah, D., Qazi, S., Khan, I. A., Abrar, M., & Zahir, S. (2024). An Effective Deep Learning-Based Approach for Splice Site Identification in Gene Expression. *Science progress*, *107*(3). https://doi.org/10.1177/00368504241266588

Angouraj Taghavi, M. (2025). Analysis of Banks' Operational Risks and the Role of Internal Audit in Reducing Them. Ninth International Conference on Outstanding Research in Management, Accounting, Banking, and Economics, Mashhad.

Atia, A. D. M., Vafaei, M., Tee, K. F., & Aliah, S. C. (2024). A Systematic Review of Structural Health Monitoring Using Artificial Neural Networks: From Traditional Neural Networks to Deep Learning Algorithms. https://doi.org/10.21203/rs.3.rs-5697583/v1

Bakhtiari, M., & Yaghoobpour, S. (2024). Examining the Relationship Between Risk Governance Mechanisms and Risk-Taking Behavior in the Banking Industry. *Journal of Islamic Economics and Banking*, *13*(48), 33-59.

Begum, A., Kumar, V. D., Asghar, J., Hemalatha, D., & Arulkumaran, G. (2022). A Combined Deep CNN: LSTM With a Random Forest Approach for Breast Cancer Diagnosis. *Complexity*, *2022*(1). https://doi.org/10.1155/2022/9299621

Chaudhary, L., Girdhar, N., Sharma, D. K., Andreu-Pérez, J., Doucet, A., & Renz, M. (2024). A Review of Deep Learning Models for Twitter Sentiment Analysis: Challenges and Opportunities. *IEEE Transactions on Computational Social Systems*, *11*(3), 3550-3579. https://doi.org/10.1109/tcss.2023.3322002

Chen, W., Hussain, W., Cauteruccio, F., & Zhang, X. (2024). Deep Learning for Financial Time Series Prediction: A State-of-the-Art Review of Standalone and Hybrid Models. *Computer Modeling in Engineering & Sciences*, *139*(1), 187-224. https://doi.org/10.32604/cmes.2023.031388

Fadaei, A., Alirezaei, A., Hashemzadeh Khorasgan, G., & Fathi Hafshejani, K. (2021). Identifying Factors Affecting Financial Risk Management in the Automotive Industry Using the DEMATEL Technique. *Financial and Investment Advances*, *2*(3), 31-50.

Fallah Shams, M. F., & Siahkarzadeh, M. S. (2019). Identification, Explanation, and Prioritization of Barriers to Implementing Operational Risk Management in Iranian Banks. *Investment Knowledge*, *8*(32), 171-193.

Gonzalez-Carrasco, I., Jimenez-Marquez, J. L., Lopez-Cuadrado, J. L., & Ruiz-Mezcua, B. (2019). Automatic Detection of Relationships Between Banking Operations Using Machine Learning. *Information Sciences*, *485*, 319-346. https://doi.org/10.1016/j.ins.2019.02.030

He, Y., Zhou, Y., Qian, Y., Liu, J., Zhang, J., Liu, D., & Wu, Q. (2025). Cardioattentionnet: Advancing ECG Beat Characterization With a High-Accuracy and Portable Deep Learning Model. *Frontiers in Cardiovascular Medicine*, *11*. https://doi.org/10.3389/fcvm.2024.1473482

Jabed, M. A., & Murad, M. A. A. (2024). Crop Yield Prediction in Agriculture: A Comprehensive Review of Machine Learning and Deep Learning Approaches, With Insights for Future Research and Sustainability. *Heliyon*, *10*(24), e40836. https://doi.org/10.1016/j.heliyon.2024.e40836

Kumar, N. (2023). Integrating Multiple Modalities for Accurate Emotion Recognition: A Deep Learning Ensemble Approach. *International Research Journal of Modernization in*

Engineering Technology and Science. https://doi.org/10.56726/irjmets33651
Kwon, S. H., & Kim, J. H. (2021). Machine Learning and Urban Drainage Systems: State-of-the-Art Review. *Water*, *13*(24), 3545. https://doi.org/10.3390/w13243545
Li, W., & Hsu, C.-Y. (2022). GeoAI for Large-Scale Image Analysis and Machine Vision: Recent Progress of Artificial Intelligence in Geography. *Isprs International Journal of Geo-Information*, *11*(7), 385. https://doi.org/10.3390/ijgi11070385
Liang, Q., Huang, J., Liang, M., & Li, J. (2024). Economic Growth Targets and Bank Risk Exposure: Evidence from China. *Economic Modelling*, *135*, 106702. https://doi.org/10.1016/j.econmod.2024.106702
Liu, Z., Luo, H., Chen, P., Xia, Q., Gan, Z., & Shan, W. (2022). An Efficient Isomorphic CNN-based Prediction and Decision Framework for Financial Time Series. *Intelligent Data Analysis*, *26*(4), 893-909. https://doi.org/10.3233/ida-216142
Ljubic, B., Pavlovski, M., Gillespie, A., Rubin, D. J., Collier, G., & Obradović, Z. (2022). Systematic Review of Supervised Machine Learning Models in Prediction of Medical Conditions. https://doi.org/10.1101/2022.04.22.22274183
Mohammadi Khanqah, G., Hosseini, S. A., & Maboudi, H. R. (2025). Examining Factors Affecting Banking Industry Risks Using Thematic Analysis. *Financial Management Strategy*, *13*(4), 1-36.
Mohammadi, R. (2026). Development and Validation of a Model for Evaluating the Effect of Banking Risks on the Stability of Iran's Banking System. *Dynamic Management and Business Analysis*, 1-18. https://www.dmbaj.com/index.php/dmba/article/view/272
Mostafaei Dolatabad, K., Azar, A., & Moghbel Baarez, A. (2018). Identifying and Analyzing Operational Risks Using Fuzzy Cognitive Mapping. *Journal of Asset Management and Financing*, *6*(4), 1-18.
Munguía-Siu, A., Vergara, I., & Espinoza-Rodríguez, J. H. (2024). The Use of Hybrid CNN-RNN Deep Learning Models to Discriminate Tumor Tissue in Dynamic Breast Thermography. *Journal of Imaging*, *10*(12), 329. https://doi.org/10.3390/jimaging10120329
Naderi, H., & Rastegar, M. A. (2022). Applying the Meta-Synthesis Method in Banking Operational Risk Management Methodology. *Asset Management and Financing*, *10*(4), 115-132.
Naderi, H., Rastegar Sorkheh, M. A., Estadi, B., & Kargari, M. (2025). Predicting the Probability of Operational Risk Occurrence in the Banking Industry Using Machine Learning Algorithms. *Asset Management and Financing*, *13*(4), 77-96.
Nosrati, P., Ahmadi, H., & Kamali Rad, E. (2025). Examining the Effect of Corporate Governance Mechanisms and Banks' Social Responsibility on Types of Bank Risk-Taking: Evidence from the Tehran Stock Exchange. *Accounting and Management Perspective*, *8*(102), 264-278.
Pena, A., Patino, A., Chiclana, F., Caraffini, F., Gongora, M., Gonzalez-Ruiz, J. D., & Duque-Grisales, E. (2021). Fuzzy Convolutional Deep-Learning Model to Estimate the Operational Risk Capital Using Multi-Source Risk Events. *Applied Soft Computing*, *107*, 107381. https://doi.org/10.1016/j.asoc.2021.107381
Pham, H. H., Khoudour, L., Crouzil, A., Zegers, P., & Velastín, S. A. (2022). Video-Based Human Action Recognition Using Deep Learning: A Review. https://doi.org/10.48550/arxiv.2208.03775
Qamar, W. U. R. (2025). Deep Learning in Intracranial EEG for Seizure Detection: Advances, Challenges, and Clinical Applications. *Frontiers in Neuroscience*, *19*. https://doi.org/10.3389/fnins.2025.1677898
Ramaswamy, S. L., & Jayakumar, C. (2023). Review on Positional Significance of LSTM and CNN in the Multilayer Deep Neural Architecture for Efficient Sentiment Classification. *Journal of Intelligent & Fuzzy Systems*, *45*(4), 6077-6105. https://doi.org/10.3233/jifs-230917
Ranjbarzadeh, R., Dorosti, S., Ghoushchi, S. J., Caputo, A., Tırkolaee, E. B., Ali, S. S., Arshadi, Z., & Bendechache, M. (2023). Breast Tumor Localization and Segmentation Using Machine Learning Techniques: Overview of Datasets, Findings, and Methods. *Computers in Biology and Medicine*, *152*, 106443. https://doi.org/10.1016/j.compbiomed.2022.106443
Roy, B., Malviya, L., Kumar, R., Mal, S., Kumar, A., Bhowmik, T., & Hu, J. W. (2023). Hybrid Deep Learning Approach for Stress Detection Using Decomposed EEG Signals. *Diagnostics*, *13*(11), 1936. https://doi.org/10.3390/diagnostics13111936
Sadeghi Amroabadi, B., & Yazdani, M. (2020). Identification and Assessment of Operational Risk in the Process of Information Management, Communications, and Customer Service Activities of Ansar Bank. *Journal of Islamic Economics and Banking*, *9*(31), 221-246.
Sadia, H., Farhan, S., Haq, Y. U., Sana, R., Mahmood, T., Bahaj, S. A., & Khan, A. R. (2024). Intrusion Detection System for Wireless Sensor Networks: A Machine Learning Based Approach. *IEEE Access*, *12*, 52565-52582. https://doi.org/10.1109/access.2024.3380014
Salih, A. A., Ameen, S. Y., Zeebaree, S. R. M., Sadeeq, M. A. M., Kak, S. F., Omar, N., Ibrahim, I. M., Yasin, H. M., Rashid, Z. N., & Ageed, Z. S. (2021). Deep Learning Approaches for Intrusion Detection. *Asian Journal of Research in Computer Science*, 50-64. https://doi.org/10.9734/ajrcos/2021/v9i430229
Selvarani, R. V., & Jose, P. S. H. (2023). A Label-Free Marker Based Breast Cancer Detection Using Hybrid Deep Learning Models and Raman Spectroscopy. *Trends in Sciences*, *20*(4), 6299. https://doi.org/10.48048/tis.2023.6299
Shafiei, S., Khan-Mohammadi, M. H., Karami, A., & Gharghi, M. (2022). The Role of Operational Risk Event Databases in Bank Risk Management. *Financial and Investment Advances*, *3*(6), 153-178.
Shoja, M., Kharazmi, O. A., & Ajza Shokouhi, M. (2021). Prioritizing and Systematically Examining the Relationships Among Dimensions of Human Resource Operational Risk. *Improvement and transformation management studies*, *30*(99), 103-133.
Wang, J., Sun, P., Chen, L., Yang, J., Liu, Z., & Lian, H. (2023). Recent Advances of Deep Learning in Geological Hazard Forecasting. *Computer Modeling in Engineering & Sciences*, *137*(2), 1381-1418. https://doi.org/10.32604/cmes.2023.023693
Wang, X., Ren, Y., Luo, Z., He, W., Hong, J., & Huang, Y. (2023). Deep Learning-Based EEG Emotion Recognition: Current Trends and Future Perspectives. *Frontiers in psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1126994
Wu, Y. (2024). Deep Learning for Cardiovascular Disease Prediction: Recent Advances, Challenges and Future Directions. *Theoretical and Natural Science*, *62*(1), 24-32. https://doi.org/10.54254/2753-8818/62/20241458
Zhang, X., Guo, F., Chen, T., Pan, L., Beliakov, G., & Wu, J. Z. (2023). A Brief Survey of Machine Learning and Deep Learning Techniques for E-Commerce Research. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(4), 2188-2216. https://doi.org/10.3390/jtaer18040110

Zhang, Z., Li, G., Xu, Y., & Tang, X. (2021). Application of Artificial Intelligence in the MRI Classification Task of Human Brain Neurological and Psychiatric Diseases: A Scoping Review. *Diagnostics*, *11*(8), 1402. https://doi.org/10.3390/diagnostics11081402

Zheng, Y., Xu, Z., & Xiao, A. (2023). Deep Learning in Economics: A Systematic and Critical Review. *Artificial Intelligence Review*, *56*(9), 9497-9539. https://doi.org/10.1007/s10462-022-10272-8

Zhou, F., Qi, X., Xiao, C., & Wang, J. (2021). MetaRisk: Semi-Supervised Few-Shot Operational Risk Classification in Banking Industry. *Information Sciences*, *552*, 1-16. https://doi.org/10.1016/j.ins.2020.11.027