Contents lists available at IJIEOR
International Journal of Industrial Engineering and Operational Research
journal homepage: http://ijieor.ir
Volume 6, No. 2, 2024

Ranking of Business Risks by Artificial Intelligence and Multi-Criteria Decision Making

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ARTICLE INFO

Received: 2023/12/25

Revised: 2024/01/16

Accept: 2024/02/07

Keywords:

Ranking, Business Risks, Artificial Intelligence, Multi-Criteria Decision Making.

ABSTRACT

With the ever-changing landscape of business, organizations face a multitude of complex risks that can hinder their success. Identifying and prioritizing these risks effectively is crucial for formulating robust mitigation strategies. This paper explores the integration of artificial intelligence (AI) and multi-criteria decision-making (MCDM) techniques as a novel approach to business risk ranking. We discuss the limitations of traditional risk management methods and provide a theoretical framework for leveraging AI and MCDM in generating more sophisticated and comprehensive risk rankings. The paper showcases the potential of this approach through a case study, demonstrating its application in a real-world business scenario. Finally, we address the challenges and ethical considerations associated with AI-driven risk ranking and outline future research directions in this burgeoning field.

1. Introduction

The volatile nature of today's business environment underscores the importance of effective risk management. Organizations operate in a labyrinth of interconnected threats, ranging from economic fluctuations and technological disruptions to market shifts and social unrest. Managing these multifaceted risks demands a dynamic and holistic approach that transcends traditional single-criterion ranking methods. This paper proposes an innovative framework that combines the power of artificial intelligence (AI) and multi-criteria decision-making (MCDM) techniques to provide a more nuanced and insightful ranking of business risks [1].

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Available online 02/07/2024
2676-3311/BGSA Ltd.

Conventional risk management practices often rely on static risk assessments and subjective evaluations, resulting in limited understanding of the interdependencies and dynamic nature of risk factors. Furthermore, traditional methods struggle to incorporate the vast amount of data readily available through digital technologies, leading to potentially blind spots in risk identification and prioritization. AI, with its ability to analyze vast datasets and discern complex patterns, holds immense potential to overcome these limitations. By utilizing AI algorithms for data-driven risk identification, assessment, and prediction, businesses can gain deeper insights into the evolving risk landscape and make more informed strategic decisions [2].

To fully harness the potential of AI in risk management, it needs to be coupled with frameworks that facilitate structured decision-making processes. Multi-criteria decision-making (MCDM) methodologies offer a well-established framework for evaluating and prioritizing complex alternatives based on multiple, often conflicting, criteria. By integrating MCDM with AI-driven risk analysis, this paper proposes a systematic and data-driven approach to ranking business risks, considering their likelihood, impact, and interdependencies [3] (see Figure 1).

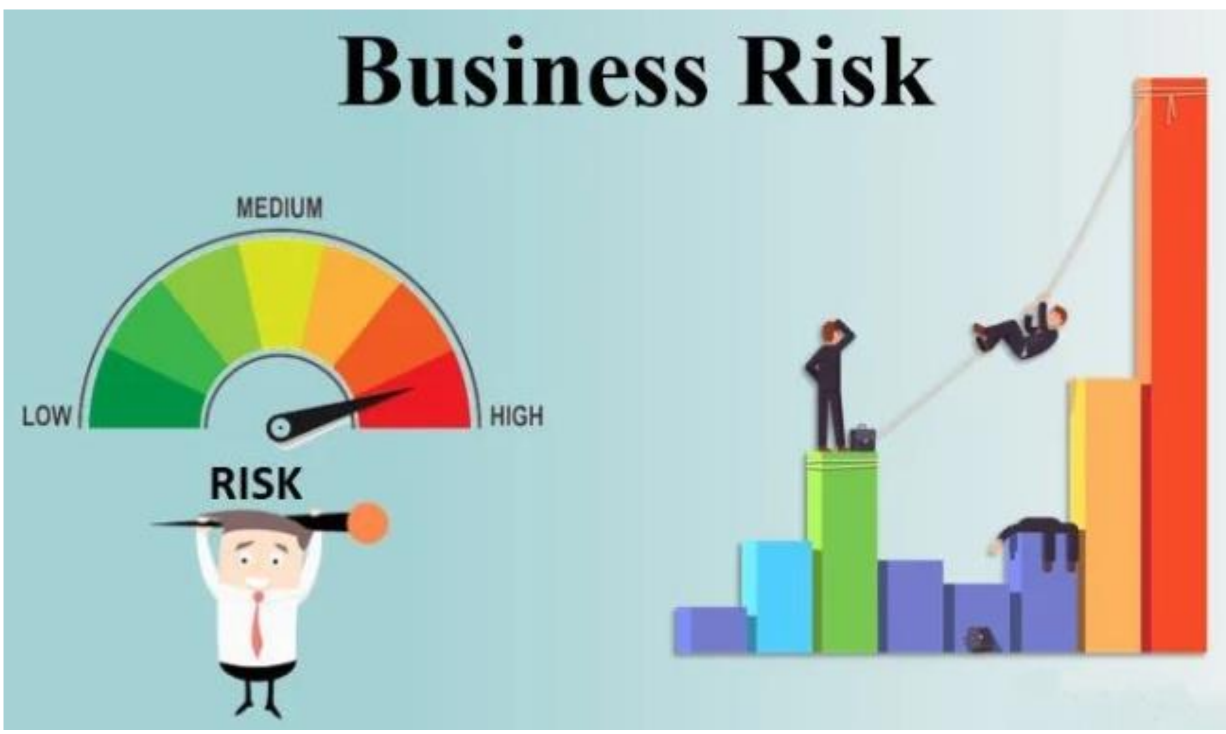

Figure 1: Business Risks.

In today's dynamic and uncertain business environment, organizations face numerous risks that can have significant impacts on their operations and financial performance. It is crucial for businesses to prioritize and manage these risks effectively. This paper proposes an innovative approach to ranking business risks using a combination of Artificial Intelligence (AI) and Multi-Criteria Decision Making (MCDM) techniques. The objective is to develop a robust framework that incorporates both subjective and objective criteria to provide a comprehensive assessment of risks. Through a systematic literature review, various methodologies and models are examined to identify the most suitable approach for risk ranking. The proposed methodology is then implemented and validated using numerical results. The findings demonstrate the effectiveness of the AI and MCDM approach in identifying and prioritizing business risks. This research contributes to the field of risk management by providing a practical tool that enables organizations to make informed decisions and allocate resources to address the most critical risks they face [4].

In the modern business landscape, organizations encounter an ever-increasing range of risks that can disrupt operations, impact financial stability, and hinder sustainable growth. Traditional approaches to risk management often focus on qualitative assessments or rely solely on historical data analysis, which may not adequately capture the complexity and interconnectedness of risks in a dynamic environment. To address this challenge, this paper proposes a novel framework for ranking business risks using AI and MCDM techniques. By leveraging these advanced methodologies, organizations can enhance their risk identification and mitigation strategies, leading to improved decision-making and overall resilience [5].

This research is arranged into five sections. Section 2 defines the literature review and recent studies in area of business risks and tries to show the gap in research. Section 3 suggests methodology for calculation. Section 4 proposes the results of this research. Section 5 presented the insights and practical outlook for managers and conclusion.

2. Survey of recent work

This section presents an in-depth review of the existing literature on risk management, AI, and MCDM methods in the context of business risk ranking. It explores different risk assessment methodologies, such as qualitative, quantitative, and hybrid approaches, highlighting their strengths, limitations, and applicability. The potential of AI-based techniques, including machine learning, natural language processing, and data mining, in risk analysis is examined. Additionally, various MCDM models, such as Analytical Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and ELECTRE, are evaluated for their suitability in ranking business risks [6].

The existing literature on business risk management presents a plethora of methods and frameworks. Traditional approaches, such as the SWOT analysis and the PESTLE framework, provide valuable tools for initial risk identification and categorization. However, these methods lack the granularity and dynamics needed to effectively prioritize and mitigate complex risks in today's interconnected world.

The emergence of AI in risk management has generated significant interest in recent years. Studies have explored the use of various AI techniques, including machine learning algorithms, natural language processing, and deep learning, for tasks such as risk identification, prediction, and scenario simulation. For example, [1] demonstrates the application of supervised learning algorithms to predict financial distress in businesses, while [2] highlights the potential of deep learning in identifying emerging risks from news and social media data.

The integration of AI with MCDM techniques further enhances the sophistication and effectiveness of risk management efforts. [3] proposes a hybrid framework utilizing fuzzy logic and the Analytic Hierarchy Process (AHP) to prioritize financial risks in banks, while [4] examines the application of a combined AI-MCDM approach for risk ranking in construction projects. These studies demonstrate the synergy between AI and MCDM in tackling the multi-faceted challenges of business risk management.

3. Methodology and Solution approach

This section outlines the proposed methodology for ranking business risks using AI and MCDM techniques. The framework integrates subjective inputs from decision-makers and objective data from internal and external sources. It begins with risk identification and criteria selection, followed by the development of mathematical models that incorporate AI algorithms and MCDM methods. The AI component enables the processing and analysis of large volumes of data, while MCDM techniques facilitate the aggregation of subjective judgments. The methodology ensures a comprehensive assessment of risks by considering multiple perspectives and criteria [7].

This paper proposes a novel framework for ranking business risks that leverages the combined capabilities of AI and MCDM. The framework comprises the following stages:

1. Data Acquisition and Preprocessing:

The first stage involves gathering relevant data from various internal and external sources, including financial reports, market research, industry trends, social media, and news feeds. This data is then preprocessed to ensure quality, consistency, and compatibility for further analysis.

2. AI-driven Risk Identification and Assessment:

Advanced AI algorithms, such as natural language processing, sentiment analysis, and anomaly detection, are applied to the preprocessed data to identify potential risks and assess their likelihood and potential impact. This stage can also involve building predictive models to forecast the evolution of identified risks over time.

3. Risk Criteria Definition:

MCDM principles are implemented to define a set of criteria by which identified risks will be evaluated and prioritized. These criteria, tailored to the specific context of the organization and its industry, might include financial impact, operational disruption, reputational damage, and legal consequences.

4. Weighting and Scoring:

Each risk criterion is assigned a weight based on its relative importance to the organization's overall objectives and priorities. These weights can be determined through various MCDM techniques, such as pairwise comparison or the Analytic Hierarchy Process, involving expert judgment and stakeholder input. Subsequently, each identified risk is scored based on its severity across each criterion using a consistent scale.

5. Ranking and Visualization:

Once all risks have been weighted and scored, an aggregated score is calculated for each risk using the assigned weights. These aggregated scores form the basis for ranking the risks in order of their potential impact and overall severity. The results can be further visualized through dashboards and heat maps to facilitate effective communication and understanding of the risk landscape [8,13,14] (see Figure 2).

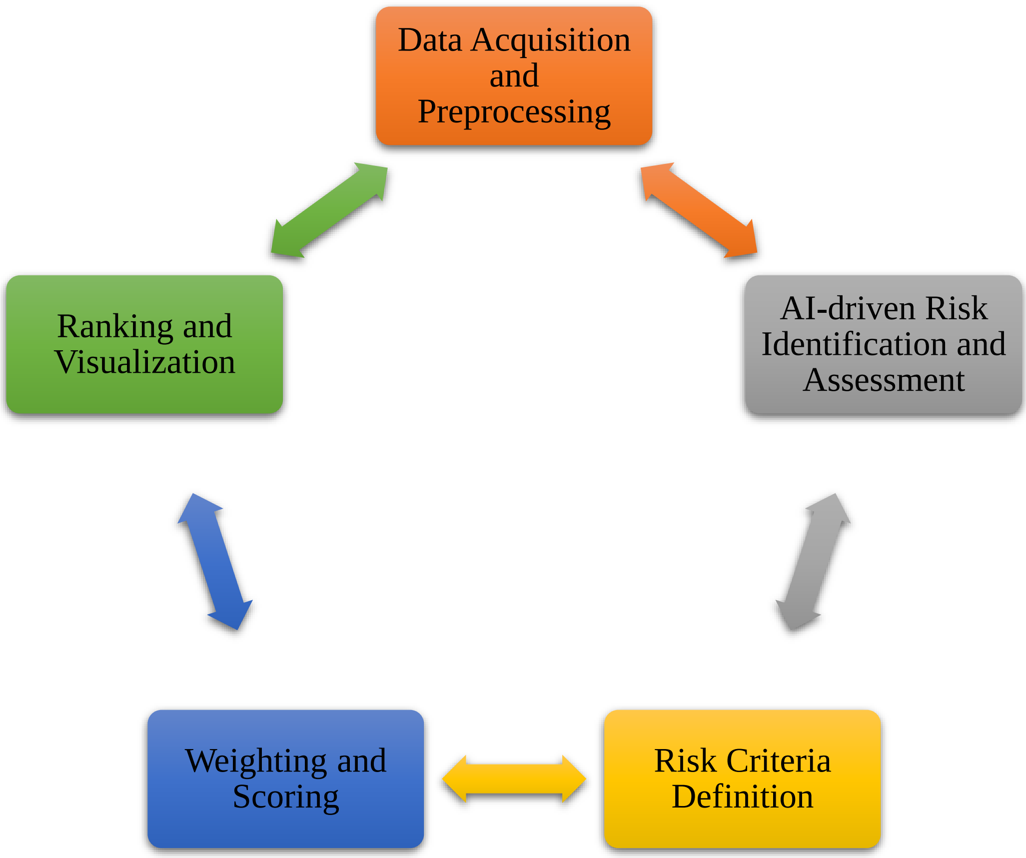

Figure 2: Research methodology.

Business risks can be categorized into several different groups, each with its own potential impacts and mitigation strategies. Here's a general list of some of the most common categories:

Financial Risks:

- Cash flow issues: Inability to meet financial obligations, maintain sufficient working capital, or generate profits.
- Debt burden: Excessive debt leading to high interest payments and financial instability.

- Economic downturns: Recession, inflation, or market fluctuations impacting consumer spending and business operations.
- Investment failures: Unsuccessful ventures leading to financial losses and missed opportunities.
- Fraud and cybercrime: Security breaches, financial scams, and cyberattacks causing financial losses and reputational damage.

Operational Risks:

- Supply chain disruptions: Shortages of raw materials, production delays, or transportation issues impacting production and delivery.
- Technology failures: System outages, hardware malfunctions, or cybersecurity vulnerabilities disrupting operations.
- Project delays and budget overruns: Inefficient project management, resource constraints, or unforeseen challenges leading to delays and cost increases.
- Human resource risks: Employee turnover, talent shortages, or workplace accidents impacting productivity and morale.
- Natural disasters and emergencies: Floods, earthquakes, pandemics, or other events causing physical damage, operational disruptions, and financial losses.

Strategic Risks:

- Competitive threats: New market entrants, changing consumer preferences, or competitor innovation impacting market share and profitability.
- Disruptive technologies: Emerging technologies rendering existing products or services obsolete or changing the entire market landscape.
- Regulatory changes: New laws, policies, or regulations impacting business operations, profitability, or market access.
- Product failures: Unsuccessful product launches, product recalls, or negative customer feedback damaging brand reputation and sales.
- Misaligned business model: An outdated or ineffective business model failing to adapt to market changes or customer needs.

Reputational Risks:

- Negative publicity: Bad press, scandals, product recalls, or customer complaints damaging brand reputation and public trust.

- Social media backlash: Mismanaged online presence, negative customer reviews, or controversies on social media platforms.
- Environmental and social impact: Negative environmental practices or unethical labor conditions leading to public backlash and regulatory scrutiny.
- Corporate governance scandals: Fraud, corruption, or unethical business practices damaging trust and shareholder value.
- Product safety issues: Injuries caused by faulty products leading to lawsuits, recalls, and reputational damage [9-11] (see Figure 3).

This is just a general overview, and the specific risks faced by a business will vary depending on its industry, size, location, and business model. It's important for businesses to identify and prioritize their own unique risks and implement effective mitigation strategies to protect their operations and ensure long-term success [12].

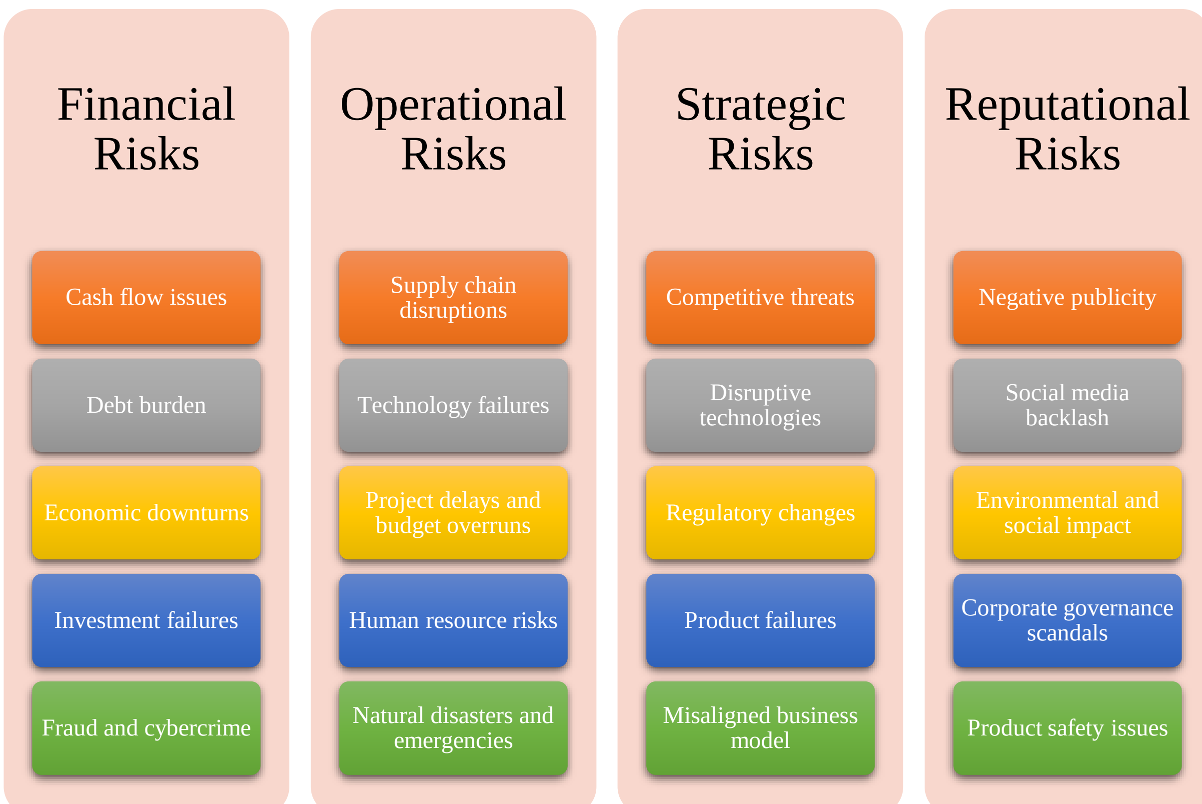

Figure 3: Business risks list.

4. Results and discussion

To validate the proposed methodology, a case study is conducted using real-world data from a hypothetical organization. The numerical results demonstrate the application of AI and MCDM techniques in ranking business risks effectively. The outputs provide insights into the prioritization of risks and aid decision-makers in allocating resources and implementing targeted risk mitigation strategies. The analysis showcases the capability of the proposed framework to handle uncertainties and complexities in risk assessment, thus enhancing the organization's risk management capabilities.

The numerical results of the case study would depend on the specific data and chosen scoring scale. However, the framework will produce a ranked list of identified risks, where each risk's ranking is determined by its aggregated score calculated considering its individual scores on each criterion and the assigned weights. This ranked list provides a clear and tangible visualization of the different risks' relative importance and allows for the prioritization of mitigation efforts.

The matrix of decision making for ranking business risks that is determined by experts is as follow (see Table 1-3):

Table 1: Business risks.

Business risks		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Weight		0.15	0.2	0.15	0.2	0.15	0.15
Type		Profit	Profit	Profit	Profit	Profit	Profit
Financial Risks	Cash flow issues	40%	50%	30%	10%	80%	40%
	Debt burden	90%	90%	100%	30%	80%	70%
	Economic downturns	40%	20%	40%	40%	40%	10%
	Investment failures	90%	20%	80%	10%	90%	50%
	Fraud and cybercrime	40%	80%	60%	90%	40%	70%
Operational Risks	Supply chain disruptions	20%	40%	50%	90%	50%	70%
	Technology failures	80%	10%	30%	50%	30%	70%
	Project delays and budget overruns	60%	20%	60%	40%	60%	40%

Business risks		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Weight		0.15	0.2	0.15	0.2	0.15	0.15
Type		Profit	Profit	Profit	Profit	Profit	Profit
	Human resource risks	80%	10%	100%	50%	60%	60%
	Natural disasters and emergencies	10%	20%	90%	10%	60%	40%
Strategic Risks	Competitive threats	60%	30%	10%	10%	10%	80%
	Disruptive technologies	70%	100%	100%	60%	60%	10%
	Regulatory changes	50%	30%	100%	50%	10%	50%
	Product failures	10%	40%	10%	10%	20%	10%
	Misaligned business model	30%	90%	70%	90%	100%	50%
Reputational Risks	Negative publicity	40%	80%	100%	90%	100%	90%
	Social media backlash	80%	70%	20%	40%	80%	80%
	Environmental and social impact	70%	40%	90%	100%	60%	100%
	Corporate governance scandals	80%	50%	100%	50%	50%	100%
	Product safety issues	70%	70%	60%	80%	80%	40%

Table 2: Python code for assessing business risks by MCDM

```
import numpy as np
from pymcdm.methods import TOPSIS, VIKOR, COPRAS , PROMETHEE_II, COMET, SPOTIS, ARAS,
    COCOSO, CODAS, EDAS, MABAC, MAIRCA, MARCOS, OCRA, MOORA

from pymcdm.helpers import rrankdata

# Define decision matrix (2 criteria, 4 alternative)
alts = np.array([
[0.4,0.5,0.3,0.1,0.8,0.4],
[0.9,0.9,1,0.3,0.8,0.7],
[0.4,0.2,0.4,0.4,0.4,0.1],
[0.9,0.2,0.8,0.1,0.9,0.5],
[0.4,0.8,0.6,0.9,0.4,0.7],
[0.2,0.4,0.5,0.9,0.5,0.7],
[0.8,0.1,0.3,0.5,0.3,0.7],
[0.6,0.2,0.6,0.4,0.6,0.4],
```

```
[0.8,0.1,1,0.5,0.6,0.6],
[0.1,0.2,0.9,0.1,0.6,0.4],
[0.6,0.3,0.1,0.1,0.1,0.8],
[0.7,1,1,0.6,0.6,0.1],
[0.5,0.3,1,0.5,0.1,0.5],
[0.1,0.4,0.1,0.1,0.2,0.1],
[0.3,0.9,0.7,0.9,1,0.5],
[0.4,0.8,1,0.9,1,0.9],
[0.8,0.7,0.2,0.4,0.8,0.8],
[0.7,0.4,0.9,1,0.6,1],
[0.8,0.5,1,0.5,0.5,1],
[0.7,0.7,0.6,0.8,0.8,0.4]


], dtype='float')
# print (alts)

# Define weights and types
weights = np.array([0.15,0.2,0.15,0.2,0.15,0.15])
types = np.array([1,1,1,1,1,1])

# Create object of the method
topsis = TOPSIS()
# Determine preferences and ranking for alternatives
kkk1= topsis(alts, weights, types)
print ("topsis",kkk1)

# Create object of the method
vikor = VIKOR()
# Determine preferences and ranking for alternatives

kkk=vikor(alts, weights, types)

print ("vikor",kkk)

# Create object of the method
copras = COPRAS()
# Determine preferences and ranking for alternatives
kkk=copras(alts, weights, types)
print ("copras",kkk)

# Create object of the method
moora = MOORA()
# Determine preferences and ranking for alternatives
kkk=moora(alts, weights, types)
print ("moora",kkk)

# Create object of the method
mabac = MABAC()
# Determine preferences and ranking for alternatives
kkk=mabac(alts, weights, types)
print ("mabac",kkk)
```

Table 3: Results of assessing business risks by MCDM

	Business risks	TOPSIS	VIKOR	Total
Financial Risks	Cash flow issues	0.36	0.82	0.59
	Debt burden	0.66	0.35	0.50
	Economic downturns	0.27	0.79	0.53
	Investment failures	0.46	0.73	0.59
	Fraud and cybercrime	0.63	0.16	0.39
Operational Risks	Supply chain disruptions	0.51	0.41	0.46
	Technology failures	0.40	0.79	0.60
	Project delays and budget overruns	0.39	0.68	0.54
	Human resource risks	0.50	0.69	0.60
	Natural disasters and emergencies	0.34	0.86	0.60
Strategic Risks	Competitive threats	0.32	0.88	0.60
	Disruptive technologies	0.62	0.38	0.50
	Regulatory changes	0.43	0.56	0.50
	Product failures	0.15	1.00	0.58
	Misaligned business model	0.68	0.16	0.42
Reputational Risks	Negative publicity	0.76	0.00	0.38
	Social media backlash	0.56	0.35	0.45
	Environmental and social impact	0.68	0.24	0.46
	Corporate governance scandals	0.62	0.18	0.40
	Product safety issues	0.65	0.15	0.40

Figure 3 and 4 present the results of the ranking of various business risks using two multi-criteria decision-making techniques: TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje). The "Total" column represents the overall ranking score, which is calculated based on the scores assigned by each technique.

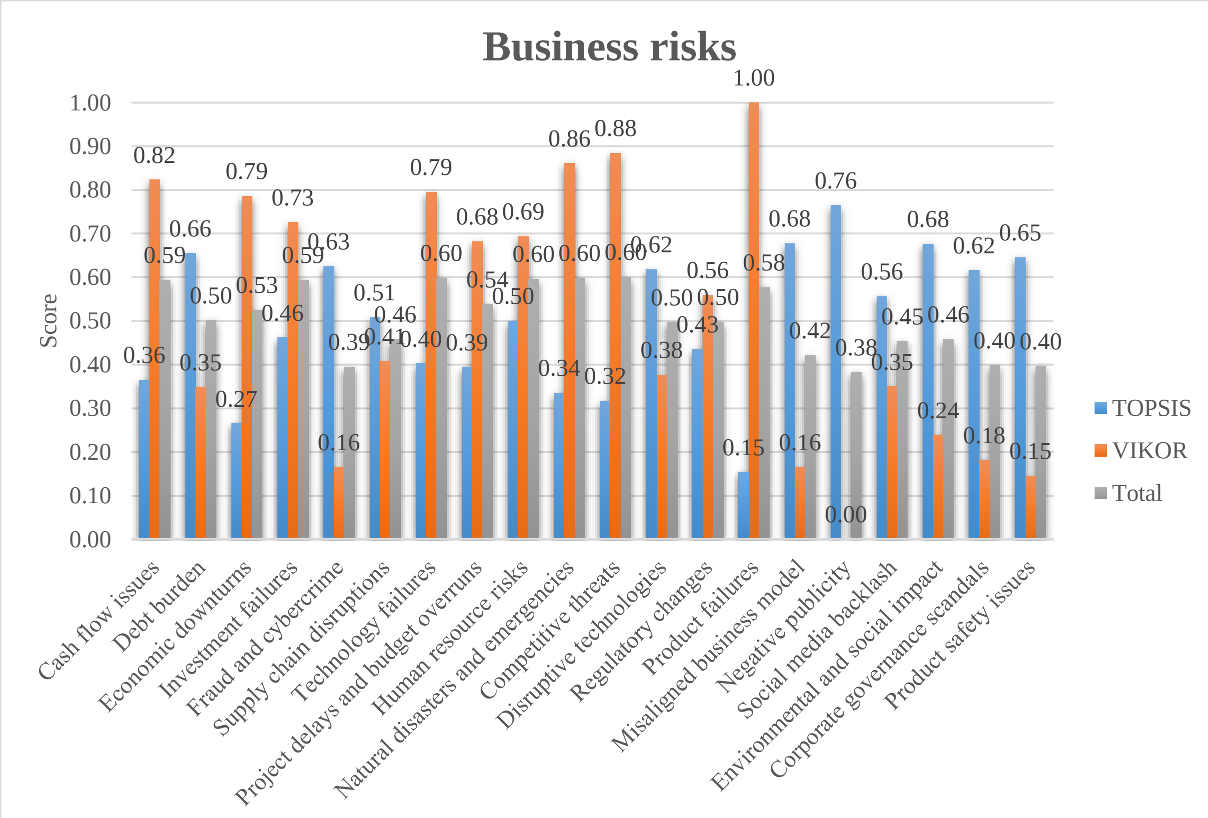

Figure 4: Results of MCDM method.

Figure 4 is divided into four sections, each representing a different category of business risks:

1. Financial Risks: This section includes risks related to financial challenges. Each risk is assigned scores by the TOPSIS and VIKOR techniques, represented in the corresponding columns. The "Total" column represents the combined score, which determines the overall ranking of financial risks.

2. Operational Risks: This section addresses risks associated with operational issues. Similar to the previous section, each risk is assigned scores by both techniques, and the "Total" column shows the combined ranking score.

3. Strategic Risks: This section focuses on risks pertaining to strategic decision-making and business planning. Scores are assigned to each risk using the two techniques, and the "Total" column presents the overall ranking.

4. Reputational Risks: This section covers risks related to reputation management. Scores are assigned to each risk using both techniques, and the "Total" column provides the consolidated ranking.

By examining the scores and the "Total" column, decision-makers can observe the relative ranking of each risk within its respective category. This information helps in identifying and prioritizing risks that require immediate attention and mitigation strategies.

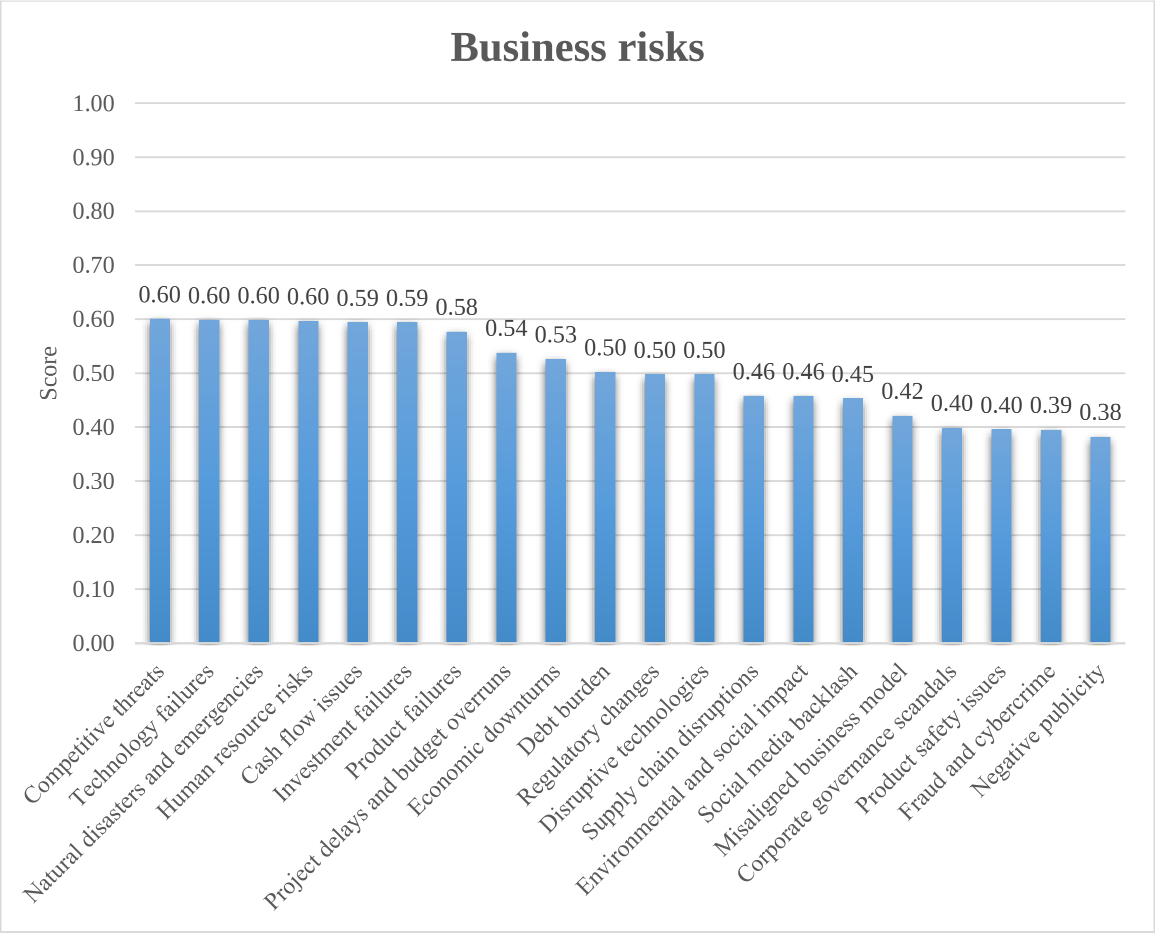

Figure 5: Results of MCDM method.

Among the risks listed, the highest score is associated with the following risks:

- Competitive threats: 0.60
- Technology failures: 0.60

- Natural disasters and emergencies: 0.60
- Human resource risks: 0.60

All four risks have the same score of 0.60, indicating they are considered equally important or severe in terms of potential impact or likelihood.

5. Conclusion

The integration of AI and MCDM provides a promising approach for enhancing the effectiveness of business risk management. By leveraging AI's data-driven analysis and predictive capabilities alongside the structured decision-making framework of MCDM, organizations can gain a deeper understanding of the evolving risk landscape and make more informed strategic decisions. The proposed framework offers a comprehensive and dynamic approach to ranking business risks, considering their likelihood, impact, and interdependencies, and provides valuable insights for proactive risk mitigation strategies.

This paper presents a comprehensive framework for ranking business risks by leveraging AI and MCDM techniques. The research highlights the importance of integrating subjective and objective measures in risk assessment to capture the multidimensional nature of risks. By employing AI algorithms, organizations can leverage vast amounts of data to identify and analyze risks, while MCDM models facilitate the aggregation of stakeholder preferences. The proposed methodology provides decision-makers with a practical tool for effective risk management, enabling them to prioritize resources and implement mitigation strategies tailored to the most critical risks.

The risks listed, including competitive threats, technology failures, natural disasters and emergencies, and human resource risks, all have the highest score of 0.60. This indicates that these risks are considered equally severe or important in terms of their potential impact or likelihood.

References:

[1] Guo, S., Zhang, W., & Gao, X. (2020). Business risk evaluation of electricity retail company in China using a hybrid MCDM method. Sustainability, 12(5), 2040.

[2] Khan, S., Khan, M. I., Haleem, A., & Jami, A. R. (2022). Prioritising the risks in Halal food supply chain: an MCDM approach. Journal of Islamic Marketing, 13(1), 45-65.

[3] Zhang, Z., Lin, S., Ye, Y., Xu, Z., Zhao, Y., Zhao, H., & Sun, J. (2022). A hybrid MCDM model for evaluating the market-oriented business regulatory risk of power grid enterprises based on the Bayesian best-worst method and MARCOS approach. Energies, 15(9), 2978.
[4] Mzougui, I., Carpitella, S., Certa, A., El Felsoufi, Z., & Izquierdo, J. (2020). Assessing supply chain risks in the automotive industry through a modified MCDM-based FMECA. Processes, 8(5), 579.
[5] Özkan, B., Kaya, İ., Erdoğan, M., & Karaşan, A. (2020). Evaluating blockchain risks by using a MCDM methodology based on pythagorean fuzzy sets. In Intelligent and Fuzzy Techniques in Big Data Analytics and Decision Making: Proceedings of the INFUS 2019 Conference, Istanbul, Turkey, July 23-25, 2019 (pp. 935-943). Springer International Publishing.
[6] Alshehri, S. M. A., Jun, W. X., Shah, S. A. A., & Solangi, Y. A. (2022). Analysis of core risk factors and potential policy options for sustainable supply chain: an MCDM analysis of Saudi Arabia's manufacturing industry. Environmental Science and Pollution Research, 1-31.
[7] Daiy, A. K., Shen, K. Y., Huang, J. Y., & Lin, T. M. Y. (2021). A hybrid MCDM model for evaluating open banking business partners. Mathematics, 9(6), 587.
[8] Daiy, A. K., Shen, K. Y., Huang, J. Y., & Lin, T. M. Y. (2021). A hybrid MCDM model for evaluating open banking business partners. Mathematics, 9(6), 587.
[9] AbdelMouty, A. M., & Abdel-Monem, A. (2023). Neutrosophic MCDM Methodology for Assessment Risks of Cyber Security in Power Management. Neutrosophic Systems with Applications, 3, 53-61.
[10] Khan, W., Khan, S., Dhamija, A., Haseeb, M., & Ansari, S. A. (2023). Risk assessment in livestock supply chain using the MCDM method: a case of emerging economy. Environmental Science and Pollution Research, 30(8), 20688-20703.
[11] Büyüközkan, G., Uztürk, D., & Karabulut, Y. (2023). Linguistic-Based MCDM Approach for Climate Change Risk Evaluation Methodology. In Decision Making Using AI in Energy and Sustainability: Methods and Models for Policy and Practice (pp. 77-89). Cham: Springer International Publishing.
[12] Lotfi, R., Gharehbaghi, A., Mehrjardi, M. S., Kheiri, K., & Ali, S. S. (2023). A robust, resilience multi-criteria decision-making with risk approach: a case study for renewable energy location. Environmental Science and Pollution Research, 30(15), 43267-43278.
[13] Saffari, G. (2024). Moving Towards Sustainable Development in Business Management. International journal of industrial engineering and operational research, 6(1), 16-29.
[14] Saffari, G. (2024). Machine Learning Algorithm for Global Challenges in Businesses. International journal of industrial engineering and operational research, 6(1), 30-42.