The Impact of Industrial Security Risk Management on Decision-Making in SMEs: A Confirmatory Factor Analysis Approach

Mohammed Amin Almaiah[1,*], Sabri Mekimah[2], Rahma Zighed[3], Tayseer Alkdour[4], Rommel AlAli[5], Rami Shehab[6,*]

[1]*King Abdullah the II IT School, The University of Jordan, Amman 11942, Jordan*

[2,3]*Ecofima Laboratory, Department of Management Sciences, University of 20 Août 1955 Skikda, Algeria*

[4]*College of Computer Science and Information Technology, King Faisal University, Al-Ahsa 31982, Saudi Arabia*

[5]*The National Research Center for Giftedness and Creativity, King Faisal University, Saudi Arabia*

[6] *Postgraduate Studies and Scientific Research, King Faisal University, Al-Ahsa 31982, Saudi Arabia*

(Received: November 18, 2024; Revised: December 14, 2024; Accepted: January 17, 2025; Available online: March 15, 2025)

Abstract

This study focuses on the importance of industrial risk management for small and medium-sized enterprises (SMEs). Risk management serves as a strategic tool that aids institutions in achieving safety and sustainability by identifying potential risks that may lead to industrial disasters, such as technical malfunctions, then analyzing, assessing, and responding to these risks in ways that minimize their impact on the safety of individuals, property, and the environment. The study aims to analyze the impact of risk management on SMEs' ability to make accurate and timely decisions and proactive risk handling. To achieve these objectives, a survey was conducted on a sample of 390 industrial SMEs. The study employed the Confirmatory Factor Analysis methodology (CB-SEM) to analyze data from these SMEs, which helped in identifying core risk management processes such as risk description, analysis, and conclusion, and evaluating their effectiveness in supporting decision-making. The findings indicate that the impact of the risk description process on decision-making is positive but weak at 14.7%, while the impact of the risk analysis process on decision-making is also positive and weak at 18.9%. However, the effect of the risk conclusion process on decision-making was positive and moderate, at 64.8%. The results further reveal that SMEs that adopt a comprehensive and sustainable approach to risk management have a greater ability to manage disasters and ensure operational safety. The study highlights the importance of regularly reviewing safety protocols, providing training and simulations for employees, improving risk response strategies, and enhancing organizational performance. The study recommends that SMEs focus on developing mechanisms for describing and analyzing risks and collaborating with specialized entities to implement modern systems that support safety and sustainability. Additionally, it advises organizations to raise employees' awareness and provide training on risk handling to enhance the effectiveness of risk management and ensure business continuity.

Keywords: Risk Description, Risk Analysis, Risk Conclusion, Decision-Making, Industrial Smes, Confirmatory Factor Analysis

1. Introduction

Industrial risk management plays a vital role in maintaining operational safety and enhancing the sustainability of industrial organizations [1], [2]. Industrial risks are defined as hazards associated with production processes and operational activities in factories and industrial plants, such as chemical leaks, fires, mechanical accidents, and technical malfunctions. Given the technological advancements and increasing complexity of industrial operations, institutions need effective risk management systems aimed at minimizing potential negative impacts on people, the environment, and property [3].

Despite ongoing efforts to improve risk management systems, challenges persist in risk assessment, incident response, and the transfer of knowledge gained from past incidents [4]. Systematic risk assessments are essential in developing proactive strategies that minimize the impact of incidents and support decision-making during critical [5], [6]. Therefore, creating integrated and targeted assessment frameworks enhances institutional efficiency in handling

***Corresponding author: Mohammed Amin Almaiah, Rami Shehab (m.almaiah@ju.edu.jo, Rtshehab@kfu.edu.sa)**
DOI: https://doi.org/10.47738/jads.v6i2.543

incidents and improving response to everyday operational challenges [6]. Industrial risk management involves several stages: identifying risks, analyzing them, assessing them, implementing appropriate responses, and finally, monitoring and evaluating post-incident performance [7]. These stages parallel disaster management phases, including prevention, preparedness, response, and recovery. Each phase requires specific actions that rely on data analysis, team coordination, and the availability of resources for effective implementation. However, the impact of each phase on the decision-making process remains an area for further research and analysis [8], [9]. This study's core issue lies in understanding how each stage of disaster management influences the quality and effectiveness of decisions made within small and medium-sized industrial enterprises (SMEs). Success in risk management relies not only on executing measures but also on utilizing information from each stage to enhance decision-making [10]. Accordingly, this research seeks to identify the relationship between disaster management phases and decision-making efficacy, focusing on factors that affect this relationship and ways to improve it through continuous evaluation and learning [11].

In this context, this paper aims to study and develop effective frameworks for industrial risk management, focusing on systematic assessments and interaction mechanisms within the industrial system. We will also explore modern risk assessment methods and ways to enhance employees' and managers' general understanding of risks to foster a safety and prevention culture within industrial institutions [12], [13]. This study is particularly important for SMEs in the literature, given the administrative, economic, and financial challenges they face [14] and the industrial risks and disasters that confront them. The study emphasizes industrial risk management as a means to improve operational safety and ensure institutional sustainability [15]. It covers essential steps, including risk identification, analysis, and conclusions, which help institutions make effective and quick decisions to manage risks and mitigate their adverse effects. This study is crucial as it offers a risk management model that considers the novelty of scholar's experience, providing a practical framework for institutions to develop preventive plans and effective responses to industrial disasters. It also highlights the importance of utilizing financial and technical resources prudently to achieve sustainability, encouraging institutions to adopt modern methods to avoid risks and meet long-term goals despite complex circumstances.

2. Literature Review

Risk management is defined as the process of identifying, assessing, and mitigating potential negative impacts of risks on operations, individuals, and the environment surrounding institutions. In the industrial context, risk management is crucial for ensuring operational safety, improving efficiency, and guaranteeing business continuity [16]. Effective mechanisms for identifying and analyzing risks allow institutions to anticipate potential threats and implement appropriate preventive strategies [17]. Risk management is also a tool for enhancing regulatory compliance and reducing costs associated with material and human losses that could result from major industrial incidents [18].

2.1. The Traditional Stages of Disaster Management

The literature highlights the traditional stages of disaster management, which include prevention, preparedness, response, and recovery: Prevention involves measures aimed at avoiding risks from the outset. In the industrial sector, prevention includes improving process design and implementing engineering and administrative controls to reduce the likelihood of accidents [19]. Preparedness focuses on developing plans and training programs for employees and establishing protocols for dealing with potential disasters. Effective preparedness can reduce the impact of incidents when they occur [20]. Response involves implementing emergency procedures during an incident to minimize losses and quickly control the situation. Effective response depends on accurate information and coordinated efforts among teams [21]. Recovery includes actions aimed at restoring operations and production to normal, such as repairing physical damage, providing psychological support to employees, and analyzing incidents to extract lessons learned [22].

2.2. Parallels between Industrial Risk Management and Disaster Management Stages

The stages of industrial risk management align closely with those of disaster management, following a similar approach in addressing potential risks and disasters, with shared objectives and core processes. Each stage in risk management corresponds to a phase in disaster management [23]. Identifying Risks: In risk management, identifying potential risks that may affect an organization—such as mechanical, chemical, or environmental hazards—is essential. This process is conducted through field inspections, data analysis, and process evaluation [24]. In disaster management, Prevention aims to reduce the likelihood of disasters by implementing preventive measures, such as safe equipment use and improved process designs. Both stages emphasize proactive measures to minimize the likelihood of risks and disasters [25]. Analyzing Risks: In industrial risk management, this stage involves analyzing the nature of risks and assessing their impact on industrial operations, including investigating root causes and estimating potential spread and safety impact [26]. In disaster management, Preparedness involves developing response plans, training employees, and preparing equipment for emergencies, reflecting a similar focus on pre-emptive actions to address and manage identified risks [27]. Evaluating Risks: In risk management, this stage involves assessing risk severity and prioritizing resources to manage the most impactful risks [28]. Similarly, in disaster management, the Response phase requires prompt action to minimize disaster impacts, relying on rapid decision-making and coordinated efforts to reduce adverse effects [29]. Implementing Responses: This stage in risk management involves executing pre-defined preventive and emergency response actions, such as additional safety systems and emergency protocols to protect assets and individuals [30]. In disaster management, Recovery aims to restore normal operations as quickly as possible by repairing damages, resuming activities, and analyzing performance. Both stages focus on restoring stability and making improvements based on lessons learned [31]. Monitoring Performance: In industrial risk management, this stage assesses the effectiveness of implemented actions, ensuring objectives are met and addressing any gaps [32]. In disaster management, Evaluation and Improvement involves extracting lessons learned and identifying improvement areas post-disaster, thus enhancing future readiness. Both stages aim to optimize the system and reduce future risks [33], [34].

2.3. Interconnected Stages of Industrial Risk Management

The stages of industrial risk management are interconnected and sequential, working together to achieve the ultimate goals of safety and sustainability [35]. Risk identification is the first and fundamental step, providing initial information on potential risks that may impact industrial operations [36]. This phase serves as the foundation for risk analysis, as effective risk identification enables a thorough analysis. During this stage, data is collected, and potential scenarios are identified, contributing to a deeper understanding of risks during analysis. The more accurate the identification, the more effective the analysis and subsequent risk management actions will be [37].

Following risk analysis, which assesses the severity and likelihood of risks, the process moves to risk evaluation. This step establishes criteria for assessing risks, such as their potential impact, frequency, and controllability [38]. Effective analysis allows for a more precise evaluation, helping to prioritize the most critical risks and supporting better decision-making regarding resource allocation and control measures [39].

Risk evaluation guides the implementation stage, where appropriate actions are identified to address risks and minimize their impact. Evaluation contributes to the formulation of preventive and response plans based on the priorities identified. The more accurate and objective the evaluation, the more effective the response strategies become. This stage provides clear information on risks that require immediate action, facilitating appropriate and timely responses [40]. Once responses are implemented, monitoring is essential to assess the effectiveness of measures taken and ensure the achievement of defined objectives [41]. The success of implementation relies on precise performance monitoring to assess whether the actions have effectively reduced risks [42]. Monitoring performance allows for continuous improvement by identifying potential shortcomings and making necessary adjustments. It also enhances future responses by providing feedback that aids in improving planning and execution [43]. The results from performance monitoring reorient the risk identification phase, where new or unexpected risks that may emerge during operations are identified. This phase depends on the system's ongoing improvement by learning from past mistakes and successes [44]. Continuous performance monitoring refines risk identification strategies, leading to a more accurate and comprehensive approach to identifying potential risks. The more effective the monitoring, the more precise future risk identification becomes.

2.4. How Industrial Risk Management Stages Impact Decision-Making

The stages of industrial risk management—risk description, risk analysis, conclusions, and decision-making are essential in informing effective decision-making and exhibit interdependencies that strengthen each subsequent phase [45]. Risk Description: This is the first and fundamental step in the process, providing initial and precise information on potential risks, such as their source, likelihood, and potential impact. This data plays a crucial role in establishing a foundation for decision-making [46].

The clearer and more comprehensive the risk description, the easier it becomes for decision-makers to understand the situation and determine the best approach. Accurate risk descriptions lead to more objective decisions based on reliable information [46]. Risk description also forms the input for risk analysis, as the quality of analysis depends on how accurately risks are described. Any inadequacy in this phase could result in incomplete or misleading analysis, hindering effective decision-making [46]. Effective communication is a vital element in risk management, as it can contribute to improving the understanding of risks and facilitating decision-making based on accurate information. Companies with open communication structures demonstrate a higher level of risk awareness and respond more effectively. Open communication within organizations can enhance risk awareness and improve small and medium-sized enterprises' responses to hazardous events.

Additionally, enhancing communication strategies can strengthen the role of risk description in the decision-making process [46]. Risk Analysis: This phase aims to assess the severity and likelihood of each risk. It provides detailed information that helps in evaluating different scenarios and prioritizing risk management actions [47]. Effective risk analysis allows decision-makers to choose the best risk management strategy, whether it involves mitigation, avoidance, or preparedness [47]. The quality of analysis is influenced by the initial risk description, as it relies on available data about the risks. Additionally, the results of this analysis feed into the next stage, Conclusions, making it a key component in forming a strong basis for decision-making [47].

Conclusions: These represent the synthesis of the analysis, providing specific recommendations for decision-makers. Conclusions clarify whether accepted risks need immediate action, improvements, or adjustments [48]. The accuracy and comprehensiveness of these conclusions directly impact decision-making, guiding decision-makers on the next steps for managing risks [48]. The quality of conclusions relies on the precision of the analysis and the information gathered in the description and analysis stages. Effective conclusions also consider multiple scenarios and provide recommendations that reinforce clarity in guiding decisions [49]. Decision-Making: This is the final phase, where decisions are made based on the foundation created by the previous stages. These decisions can range from preventive actions to immediate responses or even long-term adjustments in operations [49]. Successful decisions rely on the effectiveness of preceding stages; both risk description and analysis, along with accurate conclusions, influence the quality of the final decision [49]. If any prior stage is incomplete or inaccurate, the resulting decision may be ineffective or inappropriate for managing risks [49].

Decision-making represents the integration point of all previous stages, using the information and conclusions to form suitable actions. Any shortfall in description, analysis, or conclusions can lead to weak or ineffective decisions [49]. Small and medium-sized enterprises can adopt a range of risk mitigation strategies, including avoiding risks by eliminating activities or decisions that may expose them to danger. They can also reduce risks by implementing measures aimed at decreasing the likelihood or impact of these risks, such as improving safety protocols. Additionally, risks can be transferred by shifting the financial consequences to another party, typically through insurance contracts. Finally, risks can be accepted by acknowledging their potential impact without taking significant actions to mitigate them. These strategies help companies effectively manage risks and enhance their ability to adapt to challenges. Risk response is an integral part of the decision-making process, where appropriate strategies are identified to address discovered risks and implemented effectively. The "response" phase involves translating identified risks into actionable strategies, which is a vital component of risk management decision-making. This includes assessing the potential impact of each risk and selecting the most suitable response, such as mitigation, transfer, or acceptance [50].

Training plays a vital role in enhancing employees' skills and increasing the effectiveness of risk management. Improving employees' skills can lead to better risk responses and reduced impacts; therefore, effective training programs should be designed for small and medium-sized enterprises. These studies highlight the importance of assessing needs and tailoring programs to meet the requirements of small and medium-sized enterprises with limited resources. To enhance training programs, it is necessary to organize interactive workshops or use online learning platforms to provide ongoing and flexible training that fits employees' schedules [51]. In sum, each stage of risk management enhances the following stage and directly impacts the quality of decisions made. The more precise and thorough the preceding stages, the more effective the decisions, ultimately improving the efficiency of industrial risk management.

2.5. How Industrial Risk Management Stages Impact Decision-Making

Despite extensive literature emphasizing the importance of risk management and disaster management stages, several research gaps remain unaddressed [52]: Impact of Disaster Management Stages on Decision-Making: Many previous studies have not sufficiently explored how each stage of disaster management influences decision-making within industrial organizations. Often, the focus has been on describing processes or procedures, without analyzing their role in supporting or hindering effective decision-making [53]. Lack of Practical and Field Studies: Most studies rely on theoretical frameworks and ideal practices in risk management, with few practical experiments or field studies assessing the effectiveness of these frameworks in real industrial environments [54]. Isolated Focus on Each Disaster Management Stage: Previous research tends to address each disaster management stage individually, making it difficult to understand how these stages interact with one another to improve decision-making [55]. Limited Focus on Advanced Technology Applications: There is a shortage of research on the use of advanced technologies to support disaster management stages, particularly in preparedness and response. Although the use of smart systems and analytics is increasing, more research is needed to understand how these technologies can enhance procedural effectiveness [56]. This study aims to address these gaps by analyzing how each disaster management stage affects decision-making in small and medium-sized industrial enterprises, focusing on how decision effectiveness can be enhanced through interactive evaluation systems and continuous learning mechanisms [56].

3. Research Methodology

To achieve the study's results and determine the best model for measuring technological intelligence according to Kerr's model, Algerian startups were selected as a case study. The exploratory factor analysis (EFA) approach was applied using JASP software for first-degree factor analysis.

3.1. Analysis Techniques

A simple random sample of 390 enterprises was selected using the Thompson sampling formula, ensuring that the sample was statistically significant. Out of these, 320 responses were collected and analyzed, achieving a response rate of 82%. The simple random sample of 390 enterprises was selected using the Thompson sampling formula, as follows:

$$n = \frac{N \times p(1-p)}{[[N-1 \times (d^2 \div z^2)] + p(1-p)]} \quad (1)$$

n: population size; z: standard score corresponding to the significance level of 0.95, which equaled 1.96; d: margin of error, which equaled 0.05; p: proportion of the characteristic’s presence and neutrality = 0.50.

$$n = \frac{1{,}300{,}000 \times 0.05(1-0.05)}{[[1{,}300{,}000 - 1 \times (0.50^2 \div 1.96^2)] + 0.05(1-0.05)]} \approx 390 \quad (2)$$

Out of these, 300 questionnaires were returned and deemed analyzable, resulting in a response rate of 77%.

3.2. Research Measurements

To test the relationships between the study variables and build a valid model, a self-developed questionnaire; Steps were followed in developing the questionnaire by conducting reviews by experts in the field to ensure that the questions cover all relevant aspects of the topic. These reviews helped us make adjustments to the questionnaire items.

We conducted a pilot test of the questionnaire by distributing it to a small exploratory sample of small and medium-sized enterprises. This pilot test helped us improve the quality of the questions and participants' understanding of them, and the results were used to modify the questions and enhance their clarity. Using Likert scales and depending on the previous studies was designed, comprising 21 questions divided into 4 sections: Section One: Risk Description (Questions 1 to 6); Section Two: Risk Analysis (Questions 7 to 10); Section Three: Conclusion (Questions 11 to 16); Section Four: Decision-Making (Questions 17 to 21). In table 1, the descriptive statistics for the variables used in this research are summarized.

ISSN 2723-6471

Table 1. Descriptive statistics for the variables.

Latent Variables	Item Code	Means	Standard Deviation	R	p-Value	Statement
Risk Description	I1	2.680	1.082	0.237	0.000	Your organization has a specific plan for potential risks, such as an emergency plan and risk assessment studies.
	I2	3.487	0.992	0.312	0.000	The risk management plan aligns with the strategic objectives of your organization.
	I3	3.233	1.077	0.424	0.000	Your organization allocates a dedicated budget for avoiding potential risks.
	I4	2.793	1.127	0.381	0.000	Your organization relies on modern methods to avoid risks.
	I5	2.940	1.097	0.362	0.000	Your organization recognizes that avoiding risks helps prevent disasters.
	I6	2.910	1.167	0.385	0.000	Your organization achieves its sustainable goals despite the existence of risks.
	Tot1	2.980	4.112	0.866	0.000	Risk Description
Risk Analysis	T1	3.247	1.254	0.308	0.000	Your organization responds seriously to risks as soon as they emerge.
	T2	2.970	1.167	0.349	0.000	Your organization has the capability to anticipate potential risks.
	T3	2.993	1.077	0.301	0.000	Your organization estimates the potential loss value from risks.
	T4	3.753	1.061	0.381	0.000	Your organization accurately determines the financial value of investments exposed to risks.
	Tot2	3.301	1.116	0.345	0.000	Risk Analysis
Conclusion	Ta1	3.070	1.104	0.336	0.000	Your organization performs well in facing any risk.
	Ta2	2.973	1.116	0.311	0.000	Your organization conducts periodic reviews of monitoring protocols.
	Ta3	2.863	1.130	0.313	0.000	Your organization has a list of risks with a low probability of occurrence.
	Ta4	2.870	1.143	0.277	0.000	Your organization has in-house experts for risk analysis.
	Ta5	2.927	1.178	0.317	0.000	Your organization consults external experts for risk analysis.
	Ta6	3.023	1.162	0.432	0.000	Your organization has technical and financial capabilities to control risks.
	Tot3	2.790	1.166	0.376	0.000	Risk Conclusion
Decision-Making	J1	2.727	1.160	0.354	0.000	Your organization trains its human resources in handling various risks.
	J2	2.683	1.207	0.351	0.000	Your organization develops the skills of its human resources through training and simulation to face potential risks.
	J3	3.037	1.120	0.347	0.000	Your organization has early warning systems in place to prepare for any emergencies.
	J4	2.877	1.138	0.370	0.000	Your organization has warning signals for various potential risks.
	J5	2.837	1.150	0.379	0.000	Your organization provides cards and guidelines specific to various potential risks.
	Tot4	2.993	1.098	0.356	0.000	Decision-Making

We observe from the table that the mean for each stage of risk management and decision-making achieved a moderate to high level, with values greater than 2.60, ranging between 2.79 and 3.30, at a significance level of less than 0.05. Therefore, we can say that small and medium-sized industrial enterprises use the stages of risk management and decision-making to a moderate degree. We also note a statistically significant positive relationship at a significance level of less than 0.05 between all elements of the study variables.

3.3. Normality Test

To ensure whether the study variables follow a normal distribution, the Cramer-Von Mises test was conducted. This is illustrated in the table 2.

Table 2. Cramer-Von Mises Normality Test

Variables	Cramer-Von Mises	P Value
Description	1.598	0.067
Analysis	4.592	0.116
Conclusion	1.522	0.245
Decision	1.690	0.086

We observe from Table 2 that the Cramer-Von Mises values range between (1.522 and 4.592) with a p-value greater than 0.05. From this, we can conclude that all the study variables are normally distributed, allowing us to proceed with the study and conduct the analysis using the CB-SEM methodology.

3.4. Confirmatory Factor Analysis Test using CB-SEM

The first step in the analysis before applying CB-SEM is the Confirmatory Factor Analysis (CFA), conducted using Smart PLS software to verify the conceptual structures and measurement models of the research model [20]. This can be illustrated in the table 3 below.

Table 3. Fit Indicators for Risk Management Stages

Measurement Model	X2/ df	NFI	CFI	TLI	RMSEA	GFI	SRMR	Chi-square, X2	P value
Acceptance Criterion	From 1 to 5	NFI ≥ 0.9	CFI ≥ 0.9	TLI ≥ 0.9	RMSEA ≤ 0.08	GFI ≥ 0.9	SRMR ≤ 0.08	The lower, the better	P ≤ 0.05
Risk Management Stages	2.889	0.901	0.932	0.923	0.079	0.950	0.043	582.643	0.000
Decision	achieved	achieved	achieved	achieved	achieved	achieved	achieved	achieved	Achieved

The fit indicators in the table suggest that the risk management stages measurement model is statistically valid and demonstrates a strong fit to the data. The P-value is 0.000, which is less than 0.05, indicating high statistical significance. The Chi-square value is 582.643, which is reasonable, particularly considering the small sample size. Additionally, the SRMR value is low at 0.043, indicating good fit and minimal residual variance. The GFI exceeds the required threshold with a value of 0.950, indicating that the model explains a substantial portion of the data variance. The RMSEA value is 0.079, which falls within the acceptable range (≤0.08), enhancing the model's reliability. The TLI value is 0.923, above the minimum required threshold (0.9), confirming the model's fit and improvement over the baseline model. The CFI achieves a value of 0.932, surpassing the acceptable threshold (0.9), indicating good performance compared to the independent model. The NFI achieves a value of 0.901, meeting the acceptance criterion and indicating good model fit to the data. Finally, the X2/df ratio is 2.889, falling within the acceptable range of 1 to 5, demonstrating that the model complexity is balanced with fit quality. Overall, these indicators highlight that the risk management stages measurement model is well-constructed and effectively supports decision-making processes in small and medium-sized industrial enterprises, reinforcing the model's reliability in supporting safety strategies and sustaining organizational performance.

3.5. Validity and Reliability

The second step is to estimate the structural model, conducted using the CB-SEM methodology. The results show that all model fit indices are identical to those in the CFA, and despite some minor deviations, all values are satisfactory and appropriate, thus not affecting validity. Following this, an evaluation of the measurement model is carried out by analyzing validity and reliability [44]. The results for all techniques can be seen in the table 4.

ISSN 2723-6471

Table 4. Convergent Validity and reliability for the constructs

CB-SEM				
Items	**Loading**	**Cronbach alpha**	**Composite reliability**	**AVE**
Description				
I1	0.502	0.886	0.898	0.593
I2	0.589			
I3	0.864			
I4	0.846			
I5	0.864			
I6	0.867			
Analysis				
T1	0.770	0.811	0.841	0.574
T2	0.898			
T3	0.847			
T4	0.425			
Conclusion				
Ta1	0.752	0.913	0.913	0.638
Ta2	0.815			
Ta3	0.856			
Ta4	0.785			
Ta5	0.851			
Ta6	0.724			
Decision				
J1	0.846	0.927	0.928	0.720
J2	0.880			
J3	0.804			
J4	0.870			
J5	0.842			

We observe from the table that all loading factors (saturations) are significantly high, greater than (0.70) for all variables, with some exceptions where three items had outer loadings below (0.70). However, these items were retained as they did not affect the model's validity. All AVE values exceeded the recommended threshold (0.50), indicating that each construct explains more than 50% of the variance in its indicators, thus confirming convergent validity across all techniques. The Cronbach's Alpha and Composite Reliability values were all above the recommended threshold (0.70), which is statistically acceptable and indicates the reliability of the constructs [48].

3.6. Measures of Sampling Adequacy (MSA)

This criterion is used to assess the independence of latent variables, also known as dimensional overlap, where the relationship value between a latent variable and itself should be greater than the relationship with any other latent variable [48]. The study results according to the Fornell-Larcker criterion were represented as a matrix as follows in table 5.

Table 5. Discriminant Validity according to Fornell-Larcker criterion

Fornell-Larcker criterion				
	Analysis	**Conclusion**	**Decision**	**Description**
Analysis	0.820			
Conclusion	0.782	0.922		
Decision	0.758	0.799	0.849	
Description	0.789	0.809	0.828	0.770

From the table, we observe that for all latent variables, the value of the relationship with itself is greater than the value of the relationship with other latent variables, indicating that the latent variables are independent.

ISSN 2723-6471

3.7. HTMT Criterion Test

The HTMT criterion measures the ratio of inter-construct correlations to intra-construct correlations. For an acceptable model, no path coefficient should exceed a value of (0.90). If a path coefficient is greater than (0.90), it indicates that the constructs are theoretically very similar [43]. The study results according to the HTMT criterion were as follows in table 6:

Table 6. Discriminant Validity according to HTMT criterion

HTMT criterion				
	Analysis	**Conclusion**	**Decision**	**Description**
Analysis				
Conclusion	0.829			
Decision	0.863	0.826		
Description	0.849	0.826	0.833	

From the table, we observe that all values are not close to 1, ranging between (0.829 and 0.863), thereby meeting the criterion, and indicating that there are no theoretically similar constructs.

3.8. Structural Model of the Study: Structural Model Coefficient

After verifying the validity of the model through the assessment of construct validity and reliability, we move on to the second phase, which involves evaluating the structural model. This phase aims to examine the model's predictive capabilities and the relationships between constructs, using specific indicators. The structural model of the study is represented as follows in figure 1.

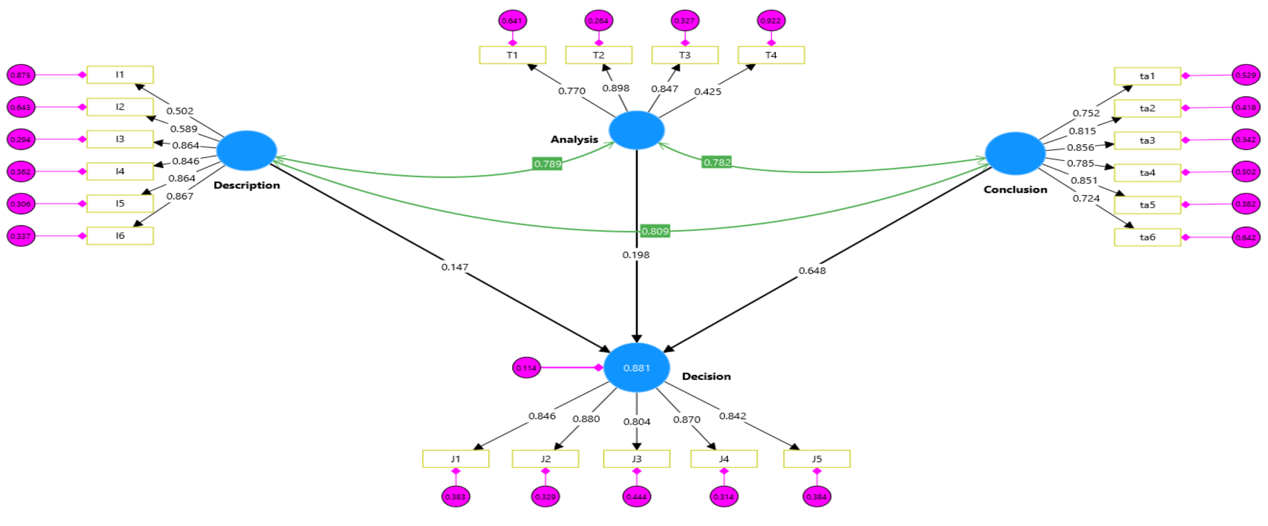

Figure 1. Path diagram with standardized estimates (CB-SEM)

From the figure, we observe that all correlation coefficients between items and latent variables were high. The relationship between the stages of Risk Description and Risk Analysis was strong, estimated at (78.9). The relationship between Risk Analysis and Risk Conclusion was also high, estimated at (78.2), while the relationship between Risk Description and Risk Conclusion was estimated at (80.9).

3.9. Path Analysis

By estimating the relationships within the structural model, which represents the hypothesized relationships between constructs, the statistical significance of all relationships is tested using T-values, P-values (less than 5%), and path coefficients. The study results for testing the significance of coefficients are presented as follows in table 7.

Table 7. Structural model coefficient

CB-SEM			
Structural model analysis	**Path coefficient**	**T values**	**P values**
Description → Decision	0.147	2.212	0.028
Analysis → Decision	0.198	3.163	0.002
Conclusion → Decision	0.648	8.803	0.000

From the table, we observe that the relationship between Risk Description and Decision-Making in small and medium-sized industrial enterprises is statistically significant at a 0.05 significance level, with a p-value of (0.028). The calculated T-value was (2.212), which is greater than the critical T-value (1.948). Additionally, the path coefficient (O) for the effect of Risk Description on Decision-Making is positive, at (0.147), indicating a positive but weak effect. Therefore, the impact of Risk Description on Decision-Making in industrial SMEs is positive but weak. Similarly, we observe from the table that the relationship between Risk Analysis and Decision-Making in small and medium-sized industrial enterprises is statistically significant at a 0.05 significance level, with a p-value of (0.002). The calculated T-value was (3.163), which is greater than the critical T-value (1.948). Additionally, the path coefficient (O) for the effect of Risk Analysis on Decision-Making is positive, at (0.189), indicating a positive but weak effect. Thus, the impact of Risk Analysis on Decision-Making in industrial SMEs is positive but weak. Finally, the table shows that the relationship between Risk Conclusion and Decision-Making in small and medium-sized industrial enterprises is statistically significant at a 0.05 significance level, with a p-value of (0.000). The calculated T-value was (8.803), which is greater than the critical T-value (1.948). Additionally, the path coefficient (O) for the effect of Risk Conclusion on Decision-Making is positive, at (0.648), indicating a positive and moderate effect. Therefore, the impact of Risk Conclusion on Decision-Making in industrial SMEs is positive and moderate.

4. Discussion of the Results

Through the analysis of theoretical literature and the practical study, we arrived at the following results:

Risk Management Components in SMEs: Risk management in small and medium-sized industrial enterprises consists of three processes: risk description, risk analysis, and risk conclusion. This structure supports the theoretical framework on which our study is based. Our results showed that the hierarchical structure of risk management operations provides a good fit to the data. Using the Confirmatory Factor Analysis methodology (CB-SEM), we found that these three processes constitute first-level factors, with risk management serving as the overarching factor. Small and medium-sized industrial enterprises precisely determine the financial value of investments at risk, train their human resources in risk handling, and develop their capabilities through training and simulations to face potential threats. This aligns with the findings of [7], which indicated that organizations invest in training and development to prepare staff for real and secure environments, reinforcing a culture of learning and future development.

Significance of Risk Conclusion in SMEs: Risk management significantly enhances the risk conclusion process, as SMEs aim to improve overall capabilities, train their personnel to handle risks, and strengthen relationships with their environment, adapting to internal and external changes. SMEs have early warning systems and various tools to prepare for emergencies. This supports [8], who found that organizations prioritize risk conclusion over analysis or description, as it has a significant impact on decision-making. They focus on teaching employees how to respond to risks when they arise. Importance of Risk Evaluation: Risk evaluation is crucial for the success and continuity of SMEs, with a significant influence on decision-making. SMEs determine appropriate actions to address risks and mitigate their impact, allowing for the development of preventive and response plans based on identified risk priorities. This aligns with [10], who concluded that risk evaluation is essential for identifying and implementing measures associated with specific risks, finding suitable solutions, and establishing optimal strategies to mitigate or eliminate risks and prevent recurrence. Role of Risk Management in Achieving Strategic Goals: Risk management plays an essential role in achieving strategic objectives for SMEs, as these organizations use risk plans aligned with their strategic goals. This finding is consistent with [12], who highlighted that organizations create plans covering both internal and external risks, which impact the sustainability of industrial enterprises. It also aligns with [13], who found that risk management

ISSN 2723-6471

is crucial for the success of organizations as it affects choices that foster resilience and long-term sustainability, helping them navigate the challenges and complexities of the business world.

Continuous Challenges in Risk Assessment: SMEs continue to face challenges related to risk assessment, incident response, and risk mitigation. This aligns with [7], who found that SMEs use risk analysis as a driver for proactive risk assessment behaviors and possess comprehensive systems that enable them to achieve desired performance levels, helping them remain competitive in the market and effectively mitigate risks. It is also in agreement with [10], who found that SMEs actively identify, analyze, respond to, and mitigate risks before they cause harm, with these organizations navigating both the challenges and opportunities in risk management. There is a positive but weak impact of the Risk Description process on decision-making in small and medium-sized industrial enterprises. This is due to the fact that these organizations lack a specific risk management plan, such as an emergency plan, risk assessment, or contingency studies. This differs from [11], which found that organizations possess emergency response systems, including fire, ambulance, and police services, which help them achieve optimal performance and make better decisions regarding risk. Additionally, they do not rely on modern methods nor recognize the importance of risk avoidance, which also contributes to the inability of these SMEs to achieve their sustainable goals in the face of risks, often leading to disaster. This aligns with [13], which concluded that SMEs possess sufficient knowledge of future events and allocate budgets to avoid expected risks. It also aligns with [14], which found that organizations are flexible when facing uncertain situations, are fully aware of potential risks, and have future estimations of destructive project costs. However, the degree of impact differs; in the current study, the influence was weak, with an impact rate of 14.7%, whereas in [22], the impact was high. This also contrasts with [20], which found that organizations are able to take necessary measures to minimize or completely eliminate risks, reducing them to an acceptable minimum.

The study found that there is a positive but weak impact of the Risk Analysis process on decision-making in SMEs. This weakness stems from the fact that these organizations do not take risks seriously as soon as they arise, differing from [21], which found that organizations take risks seriously and are fully aware of all necessary procedures to distinguish between different risk responses. They also document decisions and review plans to analyze past incidents. Additionally, SMEs lack the ability to anticipate risks or estimate the potential losses they might cause, which contrasts with [20], where organizations were found to have the capability to anticipate risks, assess risk levels, and evaluate potential losses. They also conduct vulnerability assessments in risk scenarios and devise methods to address possible threats or weaknesses. This also contrasts with [21], which found that organizations possess a strong ability to anticipate risks to achieve their strategic goals in both the short and long term. There is a positive and moderate impact of the Risk Conclusion process on decision-making in SMEs. This is because these organizations do not sufficiently rely on periodic reviews of monitoring protocols and do not maintain a list of low-probability risks. Furthermore, they neither employ nor consult internal and external experts for risk analysis, which differs from [21], which found that organizations extensively use risk assessment activities by designing controls and implementing appropriate security measures to mitigate or eliminate risks during the risk treatment process, regardless of the type of risk. This also contrasts with [21], which found that organizations use guidelines that assist employees in improving their work, especially by referencing the standards used to reach conclusions and by relying on both internal and external experts for risk analysis.

Based on the discussion of the previous results, we recommend that small and medium-sized industrial enterprises (SMEs) prioritize risk management, as it plays a vital role in maintaining operational safety and enhancing the sustainability of industrial institutions. They should also focus on Risk Conclusion as a critical element of their strategic approach and a necessary tool for making optimal decisions regarding the steps to be taken to handle risks. It is essential to consider multiple scenarios that arise from risk analysis, which strengthens their ability to guide decisions effectively and clearly. SMEs should also maintain a list of low-probability risks and demonstrate strong performance in managing any risk. They should consult internal and external experts for risk analysis, possess the technical and financial capabilities to control risks, and conduct regular reviews of their monitoring protocols. Additionally, SMEs should give proper attention to the Risk Description process, as it is the foundational step in risk management and serves as the primary input for the risk analysis phase. Providing initial, accurate information about potential risks—such as the risk source, likelihood, and potential impact—plays a crucial role in establishing a solid decision-making foundation. SMEs are also advised to develop a specific plan for potential risks, such as an emergency plan and risk assessment studies, and allocate a dedicated budget for avoiding expected risks. Moreover, SMEs should recognize that avoiding risks contributes to disaster prevention and strive to meet their sustainable goals despite the presence of risks, while adopting modern methods to avoid those risks. Furthermore, SMEs should place emphasis on Risk Analysis, which is a significant input for the conclusion phase and an essential part of building a robust decision-making foundation. This can be achieved by determining the severity of the risk, assessing its likelihood, and evaluating its potential impact. SMEs should provide detailed information that helps evaluate different scenarios and prioritize risk management actions. Additionally, SMEs need to treat risks seriously as soon as they arise, develop the full capacity to anticipate risks, and accurately determine the financial value of investments exposed to risk. They should also have a comprehensive understanding of the potential losses associated with risks, and SMEs should enhance their organizational culture to support risk management, such as promoting participative leadership and encouraging open communication about risks. We also recommend the necessity of using artificial intelligence for predictive analytics and real-time data processing to support decision-making and reduce human errors, as well as improving cybersecurity and analyzing market data to predict potential risks and respond swiftly. Additionally, we recommend enhancing communication regarding risks within these organizations by organizing regular workshops to discuss potential risks and updates on mitigation strategies, which will help engage all employees in the risk management process.

5. Conclusion

This study explores the significance of industrial risk management for SMEs in Algeria, considering the increasing economic, administrative, and technical challenges facing these institutions. The study reviewed the stages of risk management, including identifying risks, analyzing them, determining necessary actions, and understanding how these institutions respond to industrial risks and disasters that may affect their safety and sustainability. Using the Confirmatory Factor Analysis methodology (CB-SEM), data from a sample of Algerian SMEs was analyzed to assess the impact of risk management on strategic decision-making in industrial institutions. The findings reveal that SMEs adopting a comprehensive risk management approach are more likely to achieve greater resilience and long-term sustainability in the face of risks and disasters.

In light of these results, it is clear that risk management is an essential tool that enables SMEs to enhance safety and reduce the likelihood of industrial disasters. The study highlights the need for institutions to adopt a systematic and comprehensive approach to risk management, which includes developing preventive plans, training employees, and allocating an independent budget for risk handling. To increase the effectiveness of this approach, the study recommends that institutions focus on improving risk description and analysis processes, collaborate with internal and external experts, and regularly review safety protocols. By doing so, SMEs can improve their crisis response, adapt to changes, and ensure continuity and sustainable growth.

5.1. Research Limitations

This study focused solely on SMEs in the literature, which may limit the generalizability of its findings if applied to countries or regions with different economic and regulatory contexts. The sample size was restricted to a specific number of SMEs in the industrial sector, which may restrict broader generalization, as results could differ in other sectors. The study primarily utilized traditional risk management methods, with limited integration of advanced technologies like artificial intelligence and predictive analytics, which could provide a more in-depth and accurate understanding of risks. Rapid economic and political changes, which could influence SMEs' risk management strategies, were not considered, particularly during economic crises or legislative shifts.

5.2. Future Works

In our future research, we plan to explore the role of organizational culture in supporting risk management and to expand the scope of our study to include other regions or countries, enabling us to test the generalizability of the results and understand the impact of regional factors on risk management. We will focus on integrating artificial intelligence and advanced technologies, such as machine learning, which may enhance institutions' ability to predict risks more accurately and improve risk response mechanisms. Additionally, we intend to incorporate qualitative data through interviews and case studies to enhance our understanding of management practices and how companies deal with risks. We aim to develop tailored recommendations for specific industries, such as information technology and

ISSN 2723-6471

manufacturing, clarifying how strategies can be customized to meet each sector's needs, including enhancing cybersecurity and improving supply chains using artificial intelligence. Our research will also expand to include additional influential factors like employee training levels and internal system structures, providing insights into how these elements affect risk management effectiveness. Furthermore, we plan to investigate factors that contribute to successful risk management in SMEs, including effective leadership, strategic planning, and innovative crisis management strategies. Conducting comparative studies between Algeria and other countries with different risk management experiences may help identify global best practices and assess their applicability locally. We also recognize the importance of studying the direct and indirect economic impacts of risk management applications on financial sustainability and economic growth in SMEs. Lastly, we will expand our research scope to include environmental and climate risks, given their increasing significance and effects on industrial sectors. This comprehensive approach will enhance our understanding of risk management and improve decision-making effectiveness in various contexts.

6. Declarations

6.1. Author Contributions

Conceptualization: M.A.A., S.M., R.Z., T.A., R.A., and R.S.; Methodology: S.M.; Software: M.A.A.; Validation: M.A.A., S.M., and R.S.; Formal Analysis: M.A.A., S.M., and R.S.; Investigation: M.A.A.; Resources: S.M.; Data Curation: S.M.; Writing Original Draft Preparation: M.A.A., S.M., and R.S.; Writing Review and Editing: S.M., M.A.A., and R.S.; Visualization: M.A.A.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

This work was supported by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia (Grant No. KFU242722).

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] S. Durst, C. Hinteregger, and M. Zieba, "The effect of environmental turbulence on cyber security risk management and organizational resilience," *Computers & Security*, vol. 137, Art. no. 103591, pp. 1-12, 2024.

[2] S. Otoom, “Risk auditing for Digital Twins in cyber physical systems: A systematic review,” *Journal of Cyber Security and Risk Auditing*, vol. 2025, no. 1, pp. 22–35, Jan. 2025, doi: 10.63180/jcsra.thestap.2025.1.3.

[3] Y. Ying and S. Jin, "Artificial intelligence and green product innovation: Moderating effect of organizational capital," *Heliyon*, vol. 10, no. 7, pp. 1-20, 2024.

[4] S. I. Oladipo, "Effective management decision making and organisational excellence: a theoretical review," *The International Journal of Business & Management*, vol. 9, no. 1, pp. 1-13, 2021.

[5] A. Alshuaibi, M. Almaayah, and A. Ali, “Machine Learning for Cybersecurity Issues : A systematic Review,” *Journal of Cyber Security and Risk Auditing*, vol. 2025, no. 1, pp. 36–46, Feb. 2025, doi: 10.63180/jcsra.thestap.2025.1.4.

[6] M. S. Ab Rahim, G. Reniers, M. Yang, and S. Bajpai, "Risk assessment methods for process safety, process security and resilience in the chemical process industry: A thorough literature review," *Journal of Loss Prevention in the Process Industries, vol. 88, no. Apr., Art*. no. 105274, pp. 1-20, 2024.

[7] A. A. Almuqren, "Cybersecurity threats, countermeasures and mitigation techniques on the IoT: Future research directions," *Journal of Cyber Security and Risk Auditing*, vol. 1, no. 1, pp. 1–11, Jan. 2025, doi: 10.63180/jcsra.thestap.2025.1.1.

[8] M. A. Hassan, S. Zardari, M. U. Farooq, M. M. Alansari, and S. A. Nagro, "Systematic analysis of risks in industry 5.0 architecture," *Applied Sciences*, vol. 14, no. 4, Art. no. 1466, pp. 1-14, 2024.

[9] R. S. Mousa and R. Shehab, "Applying risk analysis for determining threats and countermeasures in workstation domain," *Journal of Cyber Security and Risk Auditing*, vol. 2025, no. 1, pp. 12–21, Jan. 2025, doi: 10.63180/jcsra.thestap.2025.1.2.

[10] M. A. Budihardjo, F. I. Muhammad, and A. R. Rizaldianto, "Application of risk identification, risk analysis, and risk assessment in the University laboratory," in *IOP Conference Series: Materials Science and Engineering*, vol. 598, no. 1, pp. 1-19, 2019.

[11] M. Yazdi, E. Zarei, S. Adumene, and A. Beheshti, "Navigating the power of artificial intelligence in risk management: a comparative analysis," *Safety*, vol. 10, no. 2, Art. no. 42, pp. 1-14, 2024.

[12] E. A. Mezmir, "Qualitative data analysis: An overview of data reduction, data display, and interpretation," *Research on Humanities and Social Sciences*, vol. 10, no. 21, pp. 15–27, 2020.

[13] W. K. Muhlbauer and J. Murray, "Pipeline risk management," in *Handbook of Pipeline Engineering, Cham, Switzerland: Springer International Publishing*, vol. 2024, no. 1, pp. 939–957, 2024.

[14] V. Astarita, G. Guido, S. S. Haghshenas, and S. S. Haghshenas, "Risk reduction in transportation systems: the role of digital twins according to a bibliometric-based literature review," *Sustainability*, vol. 16, no. 8, Art. no. 3212, pp. 1-19, 2024.

[15] Alotaibi, R. Bin Sulaiman, and M. Almaiah, "Assessment of cybersecurity threats and defense mechanisms in wireless sensor networks," *Journal of Cyber Security and Risk Auditing*, vol. 2025, no. 1, pp. 47–59, Feb. 2025, doi: 10.63180/jcsra.thestap.2025.1.5.

[16] F. J. García-Gómez, V. F. Rosales-Prieto, A. Sánchez-Lite, J. L. Fuentes-Bargues, and C. González-Gaya, "An approach to sustainability risk assessment in industrial assets," *Sustainability*, vol. 13, no. 12, Art. no. 6538, pp. 1-12, 2021.

[17] H. Alqudah, A. Lutfi, M. Z. Al Qudah, A. F. Alshira'h, M. A. Almaiah, and M. Alrawad, "The impact of empowering internal auditors on the quality of electronic internal audits: A case of Jordanian listed services companies," *International Journal of Information Management Data Insights*, vol. 3, no. 2, Art. no. 100183, 1-20, 2023.

[18] M. Alamer and M. A. Almaiah, "Cybersecurity in smart city: A systematic mapping study," in *Proc. 2021 Int. Conf. Inf. Technol. (ICIT)*, July 2021, vol. 2021, no. Jul., pp. 719–724, 2021, *IEEE*.

[19] A. Ali, M. A. Almaiah, F. Hajjej, M. F. Pasha, O. H. Fang, R. Khan, J. Teo, and M. Zakarya, "An industrial IoT-based blockchain-enabled secure searchable encryption approach for healthcare systems using neural network," *Sensors*, vol. 22, no. 2, Art. no. 572, pp. 1-12, 2022.

[20] R. Al Nafea and M. A. Almaiah, "Cyber security threats in cloud: Literature review," in *Proc. 2021 Int. Conf. Inf. Technol. (ICIT)*, vol. 2021, no. 1, pp. 779–786, 2021, IEEE.

[21] H. Hendar, A. Ratnawati, W. M. W. A. Razak, and Z. Abdullah, "Market intelligence on business performance: The mediating role of specialized marketing capabilities," *Journal of Intelligence Studies in Busines*s, vol. 10, no. 1, pp. 42–58, 2020.

[22] M. A. Almaiah, F. Hajjej, A. Ali, M. F. Pasha, and O. Almomani, "A novel hybrid trustworthy decentralized authentication and data preservation model for digital healthcare IoT-based CPS," *Sensors*, vol. 22, no. 4, Art. no. 1448, pp. 1-12, 2022.

[23] M. A. Almaiah, A. Ali, F. Hajjej, M. F. Pasha, and M. A. Alohali, "A lightweight hybrid deep learning privacy-preserving model for FC-based industrial internet of medical things," *Sensors*, vol. 22, no. 6, Art. no. 2112, pp. 1-13, 2022.

[24] C. Khanthavudh, A. Grealish, V. Tzouvara, J. Huang, and M. Leamy, "Implementation and evaluation of recovery-oriented practice interventions for people with mental illness in Asia: An integrative review," *International Journal of Nursing Studies*, vol. 147, Art. no. 104591, no. 1-16, 2023.

[25] F. Kitsios, E. Chatzidimitriou, and M. Kamariotou, "Developing a risk analysis strategy framework for impact assessment in information security management systems: A case study in IT consulting industry," *Sustainability*, vol. 14, no. 3, Art. no. 1269, pp. 1-15, 2022.

[26] E. Altulaihan, M. A. Almaiah, and A. Aljughaiman, "Cybersecurity threats, countermeasures and mitigation techniques on the IoT: Future research directions," *Electronics*, vol. 11, no. 20, Art. no. 3330, pp. 1-12, 2022.

[27] M. Safaeian, R. Moses, E. E. Ozguven, and M. A. Dulebenets, "An optimization-based risk management framework with risk interdependence for effective disaster risk reduction," *Progress in Disaster Science*, vol. 21, Art. no. 100313, pp. 1-20, 2024.

[28] M. A. Almaiah, O. Almomani, A. Alsaaidah, S. Al-Otaibi, N. Bani-Hani, A. K. Al Hwaitat, A. Al-Zahrani, A. Lutfi, A. Bani Awad, and T. H. H. Aldhyani, "Performance investigation of principal component analysis for intrusion detection system using different support vector machine kernels," *Electronics*, vol. 11, no. 21, Art. no. 3571, pp. 1-13, 2022.

[29] M. A. Almaiah, A. Al-Zahrani, O. Almomani, and A. K. Alhwaitat, "Classification of cyber security threats on mobile devices and applications," in *Artificial Intelligence and Blockchain for Future Cybersecurity Applications, Cham: Springer International Publishing*, vol. 2021, no. 1, pp. 107-123, 2021.

[30] H. Makkawi, "The role of risk management in increasing business performance," *Proc. Int. Conf. Business Excellence*, vol. 15, no. 1, pp. 1054-1059, Dec. 2021, Walter de Gruyter GmbH.

[31] U. C. Anozie, G. Adewumi, O. E. Obafunsho, A. S. Toromade, and O. S. Olaluwoye, "Leveraging advanced technologies in Supply Chain Risk Management (SCRM) to mitigate healthcare disruptions: A comprehensive review," *World J. Adv. Res. Rev*., vol. 23, no. 1, pp. 1039-1045, 2024.

[32] S. Mekimah, "The phases of COVID-19 crisis management by the directorates of commerce in Algeria and its effect on the consumer behavior," *Rev. Econ. Bus. Stud. (REBS)*, vol. 2020, no. 26, pp. 9-28, 2020.

[33] M. N. Raheem and M. Adrees, "The effect of risk and uncertainty factors on managerial decision making," *J. Educ. Vocational Res.*, vol. 12, no. 1, pp. 30-37, 2021.

[34] M. Žitňák, M. Korenko, T. Shchur, P. Kiełbasa, Ľ. Kazán, and M. Mazur, "Risk management in manufacturing practice using the point method," *System Safety: Human-Technical Facility-Environment*, vol. 5, no. 1, pp. 1-12, 2023.

[35] O. Almomani, M. A. Almaiah, A. Alsaaidah, S. Smadi, A. H. Mohammad, and A. Althunibat, "Machine learning classifiers for network intrusion detection system: comparative study," in *Proc. 2021 Int. Conf. Information Technology (ICIT)*, vol. 2021, no. 1, pp. 440-445, 2021.

[36] S. Mohammadi, S. De Angeli, G. Boni, F. Pirlone, and S. Cattari, "Current approaches and critical issues in multi-risk recovery planning of urban areas exposed to natural hazards," *Nat. Hazards Earth Syst. Sci*., vol. 24, no. 1, pp. 79-107, 2024.

[37] E. Altulaihan, M. A. Almaiah, and A. Aljughaiman, "Anomaly detection IDS for detecting DoS attacks in IoT networks based on machine learning algorithms," *Sensors*, vol. 24, no. 2, p. 713, 2024.

[38] M. A. Almaiah, "A new scheme for detecting malicious attacks in wireless sensor networks based on blockchain technology," in *Artificial Intelligence and Blockchain for Future Cybersecurity Applications, Cham: Springer International Publishing*, vol. 2021, no. 1, pp. 217-234, 2021.

[39] M. A. Almaiah, Z. Dawahdeh, O. Almomani, A. Alsaaidah, A. Al-Khasawneh, and S. Khawatreh, "A new hybrid text encryption approach over mobile ad hoc network," *Int. J. Electr. Comput. Eng. (IJECE)*, vol. 10, no. 6, pp. 6461-6471, 2020.

[40] M. A. Almaiah, S. Al-Otaibi, R. Shishakly, L. Hassan, A. Lutfi, M. Alrawad, and O. A. Alghanam, "Investigating the role of perceived risk, perceived security and perceived trust on smart m-banking application using SEM," *Sustainability*, vol. 15, no. 13, p. 9908, 2023.

[41] A. Pinto, I. L. Nunes, and R. A. Ribeiro, "Occupational risk assessment in construction industry–Overview and reflection," *Safety Science*, vol. 49, no. 5, pp. 616-624, 2011.

[42] O. A. Farayola and O. L. Olorunfemi, "Ethical decision-making in IT governance: A review of models and frameworks," *Int. J. Sci. Res. Arch.*, vol. 11, no. 2, pp. 130-138, 2024.

[43] G. Fanti, A. Spinazzè, F. Borghi, S. Rovelli, D. Campagnolo, M. Keller, and D. M. Cavallo, "Evolution and applications of recent sensing technology for occupational risk assessment: a rapid review of the literature," *Sensors*, vol. 22, no. 13, pp. 4841-4854, 2022.

[44] A. M. Albalawi and M. A. Almaiah, "Assessing and reviewing of cyber-security threats, attacks, mitigation techniques in IoT environment," *J. Theor. Appl. Inf. Technol*., vol. 100, no. 9, pp. 2988-3011, 2022.

[45] M. AlMedires and M. Almaiah, "Cybersecurity in industrial control system (ICS)," in Proc. 2021 Int. Conf. Information Technology (ICIT), 2021, pp. 640-647.

[46] F. Almudaires and M. Almaiah, "Data an overview of cybersecurity threats on credit card companies and credit card risk mitigation," in *Proc. 2021 Int. Conf. Information Technology (ICIT)*, vol. 2021, no 1, pp. 732-738, 2021.

[47] T. S. AlSalem, M. A. Almaiah, and A. Lutfi, "Cybersecurity risk analysis in the IoT: A systematic review," *Electronics*, vol. 12, no. 18, pp. 3958-3970, 2023.

ISSN 2723-6471

[48] A. Ali, M. F. Pasha, O. H. Fang, R. Khan, M. A. Almaiah, and A. K. Al Hwaitat, "Big data based smart blockchain for information retrieval in privacy-preserving healthcare system," *in Big Data Intelligence for Smart Applications, Cham: Springer International Publishing*, vol. 2022, no. 1, pp. 279-296, 2022.

[49] M. A. Almaiah, S. Yelisetti, L. Arya, N. K. Babu Christopher, K. Kaliappan, P. Vellaisamy, and T. Alkdour, "A novel approach for improving the security of IoT–medical data systems using an enhanced dynamic Bayesian network," *Electronics*, vol. 12, no. 20, pp. 4316-4329, 2023.

[50] M. Schini, H. Johansson, N. C. Harvey, M. Lorentzon, J. A. Kanis, and E. V. McCloskey, "An overview of the use of the fracture risk assessment tool (FRAX) in osteoporosis," J. Endocrinol. Invest., vol. 47, no. 3, pp. 501-511, 2024.

[51] O. Almomani, M. A. Almaiah, M. Madi, A. Alsaaidah, M. A. Almomani, and S. Smadi, "Reconnaissance attack detection via boosting machine learning classifiers," in *AIP Conf. Proc.*, vol. 2979, no. 1, pp. 1-12, AIP Publishing, Oct. 2023.

[52] M. Alrawad, A. Lutfi, M. A. Almaiah, A. Alsyouf, H. M. Arafa, Y. Soliman, and I. A. Elshaer, "A novel framework of public risk assessment using an integrated approach based on AHP and psychometric paradigm," *Sustainability*, vol. 15, no. 13, pp. 9965-9977, 2023.

[53] D. Hanggraeni, B. Ślusarczyk, L. A. K. Sulung, and A. Subroto, "The impact of internal, external and enterprise risk management on the performance of micro, small and medium enterprises," *Sustainability*, vol. 11, no. 7, pp. 2172-2184, 2019.

[54] T. Alkdour, M. A. Almaiah, R. Shishakly, A. Lutfi, and M. Alrawad, "Exploring the success factors of smart city adoption via structural equation modeling," *Sustainability*, vol. 15, no. 22, pp. 15915-15927, 2023.

[55] N. Okechukwu, E. P. Agbai, and H. PCE, "Exploring the role of value orientation in small and medium-sized enterprise (SME) and entrepreneurial development in Nigeria," *Disseminating Scholarly Research Across The Globe*, vol. 5, no. 1, pp. 1-12, 2024.

[56] M. A. Almaiah and T. Alkdour, "Securing fog computing through consortium blockchain integration: The proof of enhanced concept (PoEC) approach," *in Recent Advancements in Multimedia Data Processing and Security: Issues, Challenges, and Techniques, IGI Global*, vol. 2023, no. 1, pp. 107-140, 2023.