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# Prioritizing Risk Mitigation Strategies in Air Cargo Freight Operations: A Fuzzy TOPSIS Approach

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**Abstract**

This study explores the prioritization of risk mitigation strategies in air cargo operations using a Fuzzy TOPSIS methodology. Air cargo operations face multifaceted risks, including operational inefficiencies, cybersecurity threats, regulatory compliance challenges, and environmental concerns. To address these, a structured decision-making framework was developed, integrating expert evaluations with fuzzy logic to rank mitigation strategies across ten criteria, such as cost-effectiveness, operational efficiency, and scalability. Enhanced Data Security Measures emerged as the top-ranked strategy, reflecting the critical importance of cybersecurity in modern logistics. Other highly prioritized strategies, including Resilience Building for Disruptions and Safety Enhancement Protocols, underscore the need for operational stability and safety in a rapidly evolving industry. The study demonstrates the practical applicability of Fuzzy TOPSIS in handling uncertainty and subjectivity in risk management while providing actionable insights for practitioners. Recommendations are offered for the implementation of prioritized strategies and the integration of emerging technologies, such as real-time analytics and AI-driven decision-making models. The findings contribute to advancing the field of risk management in air cargo operations and highlight areas for future research, including dynamic risk assessment and the integration of complementary MCDM techniques.

## 1. Introduction

Air cargo is a cornerstone of global trade, facilitating the rapid and reliable transportation of goods across international borders. Its role has become increasingly critical in an era where speed and efficiency are paramount to meeting the demands of global supply chains. From high-value electronics to perishable goods, air cargo ensures that time-sensitive products reach their destinations without delay, supporting economic growth and market competitiveness (Merkert, 2023; Sales & Scholte, 2023). The rising complexity of international commerce, driven by globalization and e-commerce, underscores the need for efficient air cargo systems. However, the sector faces significant challenges, including operational inefficiencies, delays, security breaches, and environmental concerns, which collectively threaten the seamless functioning of supply chains (Bunahri et al., 2023; Tseremoglou et al., 2022). Addressing these risks is essential for maintaining the reliability and resilience of the global logistics network.

The importance of effective risk management in air cargo operations has been highlighted by recent global crises, such as the COVID-19 pandemic, which exposed vulnerabilities in supply chains worldwide. These disruptions underscored the need for robust mitigation strategies to ensure continuity in air cargo operations and minimize the cascading effects of delays and disruptions on businesses and consumers (Hohenstein, 2022; Can Saglam et al., 2021). However, despite the growing recognition of risk management's critical role, the sector lacks structured and systematic methodologies for prioritizing risk mitigation strategies. Current approaches often fall short in addressing the complex, dynamic, and uncertain nature of air cargo operations, leaving operators ill-equipped to navigate emerging risks effectively (Sahoo et al., 2022; Dauer & Dittrich, 2022).

The inherent complexities of air cargo risk management are further compounded by the need for quick and precise decision-making in scenarios such as cargo handling optimization, disruption management, and compliance with evolving regulations. Traditional risk management frameworks struggle to accommodate these challenges, particularly in the face of rapid technological advancements and increasingly interconnected supply chain networks (Hong et al., 2025; Esmizadeh & Mellat Parast, 2021). Advanced decision-making tools, such as Multi-Criteria Decision-Making (MCDM) methodologies enhanced with fuzzy logic, offer a promising solution by systematically evaluating and ranking strategies under conditions of uncertainty.

These tools provide a nuanced and reliable approach to decision-making, capturing the inherent vagueness of expert judgments and operational complexities (Mahdavi et al., 2008; Kaya & Kahraman, 2011).

This study addresses the gap in the literature by proposing a Fuzzy TOPSIS-based model for prioritizing risk mitigation strategies in air cargo operations. The model integrates expert input with a robust analytical framework, providing a structured approach to evaluate key risks, such as operational delays, cybersecurity threats, and environmental challenges. By incorporating fuzzy logic, the model accommodates the uncertainties and ambiguities inherent in expert evaluations, ensuring a more reliable and adaptive decision-making process (Yan et al., 2022; Göçmen, 2021). The study identifies and evaluates critical risks affecting air cargo operations and develops a methodology to prioritize mitigation strategies that align with industry requirements and global trends.

The research draws on the expertise of professionals from logistics, supply chain, and risk management sectors, ensuring that the findings are both theoretically grounded and practically applicable. By focusing on the critical risks and employing a structured methodology, the study not only advances the academic discourse on risk management but also provides actionable insights for practitioners. These insights aim to enhance the resilience, efficiency, and sustainability of air cargo operations, addressing the multifaceted challenges faced by operators in today's interconnected and risk-prone environment (Richey Jr et al., 2023; Giuffrida et al., 2021). Through the prioritization of mitigation strategies, the study offers a practical framework for strengthening the robustness of air cargo operations and ensuring their continued role in supporting global trade.

## 2. Literature Review

### 2.1. Risk Factors in Air Cargo Freight Operations

Air cargo freight operations face a multitude of risks that can significantly disrupt supply chain performance. Operational risks such as cargo delays, mismanagement of cargo loads, and insufficient capacity planning are recurring issues in the air cargo industry (Sencer & Karaismailoğlu, 2022; Mesquita & Sanches, 2024). Delays, often caused by weather disruptions, mechanical failures, or inefficient terminal operations, can result in substantial financial losses and reputational damage for carriers (Han et al., 2022). Capacity mismanagement, particularly during peak demand periods, further exacerbates these challenges by creating bottlenecks and reducing operational efficiency (Gritsenko & Karpun, 2020).

Security risks, including theft, tampering, and the infiltration of contraband, present another significant challenge for air cargo operations. The high-value nature of goods transported via air freight makes these operations particularly susceptible to targeted security breaches (Sun et al., 2020). Cybersecurity threats, such as unauthorized access to cargo management systems, have also become more prevalent with the increasing digitization of logistics operations (Göçmen, 2021). The integration of advanced technologies, while improving efficiency, introduces new vulnerabilities that must be addressed through robust security protocols and monitoring systems (Mızrak & Akkartal,2023).

Environmental risks, including noise pollution, greenhouse gas emissions, and compliance with stringent environmental regulations, further complicate air cargo operations. Airports and freight carriers are under growing pressure to minimize their carbon footprints while maintaining high operational standards (Davydenko et al., 2020). Initiatives such as optimizing flight routes, adopting fuel-efficient technologies, and incorporating renewable energy sources in cargo operations have been explored to mitigate these environmental impacts (Archetti & Peirano, 2020). However, these solutions often require significant investment and strategic planning to implement effectively.

Previous studies have highlighted the importance of risk management frameworks tailored to the unique challenges of air cargo operations. For example, Dauer and Dittrich (2022) proposed an operational-risk-based approach for automated cargo delivery, emphasizing the need for scenario-specific risk assessment models. Similarly, De Oliveira et al. (2024) explored the integration of risk management practices into the import/export processes of supply chains, underscoring the interconnectedness of air cargo operations with broader logistics networks. These studies collectively emphasize the necessity for proactive and adaptive risk management strategies to ensure resilience and sustainability in air cargo operations.

### 2.2. Mitigation Strategies for Air Cargo Risks

Effective risk mitigation in air cargo operations is essential for ensuring the seamless functioning of global supply chains. Existing strategies often focus on enhancing operational efficiency, improving security protocols, and minimizing environmental impact. Proactive risk identification and real-time monitoring systems have been highlighted as critical tools for mitigating operational risks. For example, automated tracking technologies and predictive analytics are increasingly being employed to optimize cargo handling and reduce delays (Tanrıverdi et al., 2022; Angelelli et al., 2020). Additionally, the use of dynamic routing models helps carriers adapt to changing circumstances, such as adverse weather conditions or airport congestion, ensuring timely delivery (Archetti & Peirano, 2020).

In terms of security, the integration of advanced surveillance technologies and collaborative security frameworks has proven effective in mitigating threats like theft and smuggling. For instance, layered security systems that combine physical inspections with digital safeguards are widely adopted to secure high-value goods during transit (Han et al., 2022; Dauer & Dittrich, 2022). Furthermore, the application of blockchain technology for cargo documentation and tracking has been explored to enhance transparency and prevent data manipulation (Hohenstein, 2022). However, these solutions often face challenges related to scalability and interoperability across different systems and stakeholders.

To address environmental risks, air cargo operators are exploring sustainable practices, such as utilizing fuel-efficient aircraft and implementing green logistics strategies. Carbon offset programs and the adoption of alternative fuels are also gaining traction as viable solutions to meet environmental regulations and reduce emissions (Bartle et al., 2021; Davydenko et al., 2020). While these measures contribute to environmental sustainability, their implementation often involves high costs and operational adjustments, which can hinder widespread adoption.

Despite these advancements, gaps in prioritization methodologies persist. Traditional approaches to risk mitigation often rely on qualitative assessments that lack the precision and adaptability needed in dynamic air cargo environments (Mesquita & Sanches, 2024). For example, while many studies propose comprehensive risk management frameworks, they often fail to address how to prioritize multiple risks or mitigation strategies effectively. Additionally, there is limited research on incorporating expert judgment and real-time data into decision-making models (Richey Jr. et al., 2023; Kondratenko et al., 2020). The lack of structured, quantitative approaches to ranking mitigation strategies under uncertainty creates a critical gap in the literature.

Addressing these gaps requires innovative methodologies that combine multi-criteria decision-making (MCDM) tools with advanced data analytics. Fuzzy logic-based approaches, for example, offer a way to integrate subjective expert opinions with quantitative metrics, providing a more holistic framework for risk prioritization. Studies suggest that models like Fuzzy TOPSIS can bridge these gaps by evaluating and ranking mitigation strategies under uncertain and dynamic conditions, making them particularly suitable for complex systems like air cargo freight operations (Budak et al., 2020; Mahdavi et al., 2008). However, further research is needed to validate these models in practical scenarios and tailor them to the specific challenges of air cargo logistics.

### 2.3. Multi-Criteria Decision-Making (MCDM) in Risk Management

The application of Multi-Criteria Decision-Making (MCDM) methods has been pivotal in addressing the complexities of logistics and supply chain management, particularly in the domain of risk management. MCDM methodologies provide structured frameworks for evaluating multiple, often conflicting, criteria, enabling decision-makers to assess trade-offs and prioritize strategies effectively (Pournader et al., 2020; Hohenstein, 2022). In logistics and supply chain contexts, MCDM tools have been widely employed for tasks such as supplier selection, route optimization, and the prioritization of risk mitigation strategies. For instance, the Analytical Hierarchy Process (AHP) and the Best-Worst Method (BWM) have been extensively used to rank suppliers based on criteria such as cost, reliability, and environmental impact (Yalçın & Ayyıldız, 2024; Gao et al., 2023). Similarly, methods like PROMETHEE and ELECTRE have demonstrated their versatility in evaluating transportation options, showcasing their adaptability to a variety of decision-making scenarios (Tanrıverdi et al., 2022; Göçmen, 2021).

Fuzzy logic has emerged as a transformative extension to traditional MCDM methods, especially in addressing the uncertainties inherent in risk management. Conventional decision-making approaches often face challenges when dealing with imprecise or incomplete information—a common occurrence in logistics operations where subjective expert judgments play a critical role (Kaya & Kahraman, 2011; Kondratenko et al., 2020). Fuzzy logic overcomes these limitations by employing linguistic variables and fuzzy sets, enabling decision-makers to better navigate the nuances of uncertainty. For example, fuzzy extensions of AHP and TOPSIS have been employed to incorporate expert opinions and account for real-world complexities, significantly enhancing the robustness of risk assessments (Mahdavi et al., 2008; Budak et al., 2020).

Among MCDM methods, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) has gained prominence for its simplicity and efficiency in ranking alternatives. The method involves identifying the ideal and anti-ideal solutions and calculating the relative closeness of each alternative to these benchmarks (Kaya & Kahraman, 2011). Its applications span various domains, including supply chain risk management, where it has been utilized to evaluate and prioritize mitigation strategies, assess supplier performance, and optimize logistics network designs (Tanrıverdi et al., 2022; Mesquita & Sanches, 2024). Fuzzy TOPSIS, an extension of the traditional method, further enhances decision-making by accommodating uncertainty and subjectivity in criteria weights and alternative evaluations (Mahdavi et al., 2008). Budak et al. (2020) demonstrated the effectiveness of fuzzy TOPSIS in selecting real-time location systems for humanitarian logistics, highlighting its adaptability to dynamic and complex environments.

Recent advancements in the fuzzy TOPSIS method have introduced further refinements to enhance its applicability. Intuitionistic fuzzy TOPSIS, as proposed by Boran et al. (2009), extends the traditional approach by incorporating intuitionistic fuzzy sets to handle higher degrees of uncertainty and vagueness. This methodology has been particularly useful in scenarios requiring group decision-making, such as supplier selection. Additionally, q-rung orthopair fuzzy TOPSIS represents a significant evolution of the method, providing an even more flexible framework for addressing complex decision-making scenarios. Pınar (2021) applied q-rung orthopair fuzzy TOPSIS to third-party logistics provider selection, demonstrating its ability to manage intricate criteria relationships. Further developments by Pınar and Boran (2022) utilized this approach in combination with other MCDM methods, such as CODAS, to evaluate 3PL service providers, showcasing its robustness and adaptability.

While these advancements have enhanced the capabilities of the fuzzy TOPSIS method, the effective application of such techniques requires careful consideration of criteria selection and weight assignment, often necessitating expert input. By integrating fuzzy logic into TOPSIS, decision-makers can address the limitations of conventional methods and establish a robust framework for managing the uncertainties and complexities inherent in risk management. The combination of quantitative rigor with qualitative insights positions fuzzy TOPSIS as a valuable tool for enhancing operational resilience and efficiency in logistics and supply chain management.

## 3. Research Methodology

### 3.1. Study Design

This study employs a mixed-methods approach, integrating qualitative and quantitative data collection. Expert evaluations are used to identify and weight key criteria for prioritizing risk mitigation strategies. The qualitative component involves gathering expert insights through structured interviews, while the quantitative analysis applies the Fuzzy TOPSIS methodology to evaluate and rank the identified strategies, ensuring a comprehensive and systematic assessment.

While traditional methods like AHP and PROMETHEE provide robust frameworks for multi-criteria decision-making, their deterministic nature limits their effectiveness in contexts involving high uncertainty. Fuzzy TOPSIS, in contrast, incorporates fuzzy logic, allowing for a more nuanced representation of expert opinions, making it particularly suited for the complex and uncertain environment of air cargo operations. Figure 1 demonstrates the steps of the analysis.

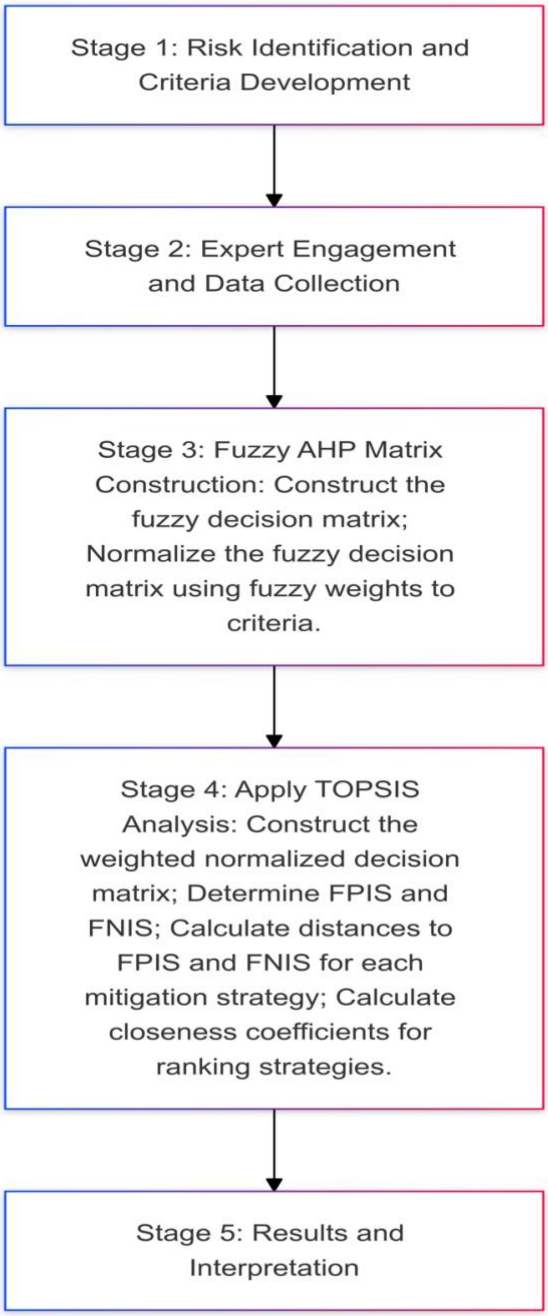


**Figure 1.** Workflow Chart

### 3.2. Identification of Risk Mitigation Criteria

The identification of appropriate risk mitigation criteria is critical for developing an effective decision-making framework. In this study, the criteria are categorized into key dimensions, including cost-effectiveness, operational efficiency, scalability, and regulatory compliance, which reflect the multifaceted nature of risk management in air cargo operations. These categories are widely recognized in the literature as essential for evaluating and prioritizing strategies in logistics and supply chain contexts (Hohenstein, 2022; Esmizadeh & Mellat Parast, 2021

Cost-effectiveness is a fundamental criterion, ensuring that mitigation strategies provide value while optimizing resource utilization. Studies emphasize the need for cost-efficient solutions, particularly in the competitive and cost-sensitive air cargo industry (Angelelli et al., 2020; Mesquita & Sanches, 2024). Similarly, operational efficiency is critical to minimizing delays, optimizing cargo handling, and enhancing overall performance, as highlighted in prior analyses of air cargo logistics (Han et al., 2022; Archetti & Peirano, 2020).

Scalability is another key criterion, particularly in addressing the dynamic nature of air cargo operations, where strategies must adapt to varying demand levels and operational scales (Tanrıverdi et al., 2022; Sencer & Karaismailoğlu, 2022). Finally, compliance with regulations is essential to mitigate risks related to security and environmental impact, ensuring adherence to international standards and enhancing organizational reputation (Davydenko et al., 2020; Bartle et al., 2021).

In addition to these primary criteria, several other factors also play a significant role in shaping risk mitigation strategies. Technology adaptability has become increasingly important in air cargo operations, as the industry increasingly relies on automation and digital technologies to optimize processes and improve efficiency. The ability of mitigation strategies to integrate with emerging technologies is crucial to maintaining operational flexibility (Tanrıverdi et al., 2022; Kondratenko et al., 2020). Environmental sustainability is another important criterion, given the growing focus on reducing the carbon footprint and meeting environmental regulations. Strategies that promote sustainability not only help mitigate risks associated with environmental impact but also improve the long-term viability of air cargo operations (Bartle et al., 2021; Davydenko et al., 2020).

Resilience to disruptions is crucial in the context of unforeseen events, such as natural disasters, strikes, or pandemics, that can disrupt air cargo operations. Mitigation strategies must enhance the ability to recover quickly from these disruptions and ensure continuity of service (Sun et al., 2020; Gritsenko & Karpun, 2020). The ease of implementation is another criterion, as it evaluates the practicality of executing mitigation strategies within the constraints of available resources and infrastructure. This factor is vital for ensuring that risk management solutions are not only effective but also feasible to implement in real-world settings (Sencer & Karaismailoğlu, 2022).

Stakeholder acceptance is essential to gauge the level of support from various parties involved, including employees, customers, and regulatory bodies. Successful risk mitigation strategies must garner the cooperation of all stakeholders to ensure their effectiveness and sustainability (Hohenstein, 2022). Lastly, safety enhancement and data security are paramount in mitigating risks related to the safety of cargo and the protection of sensitive data during transportation. The increasing use of digital platforms in air cargo operations underscores the importance of securing both physical and cyber assets (Han et al., 2022; Göçmen, 2021).

To provide a comprehensive understanding of the risks involved in air cargo operations, the following diagram categorizes risks into key types: Operational, Security, Regulatory, Environmental, and Stakeholder Risks. Each category is further broken down into specific challenges, forming the basis for risk mitigation strategy development.

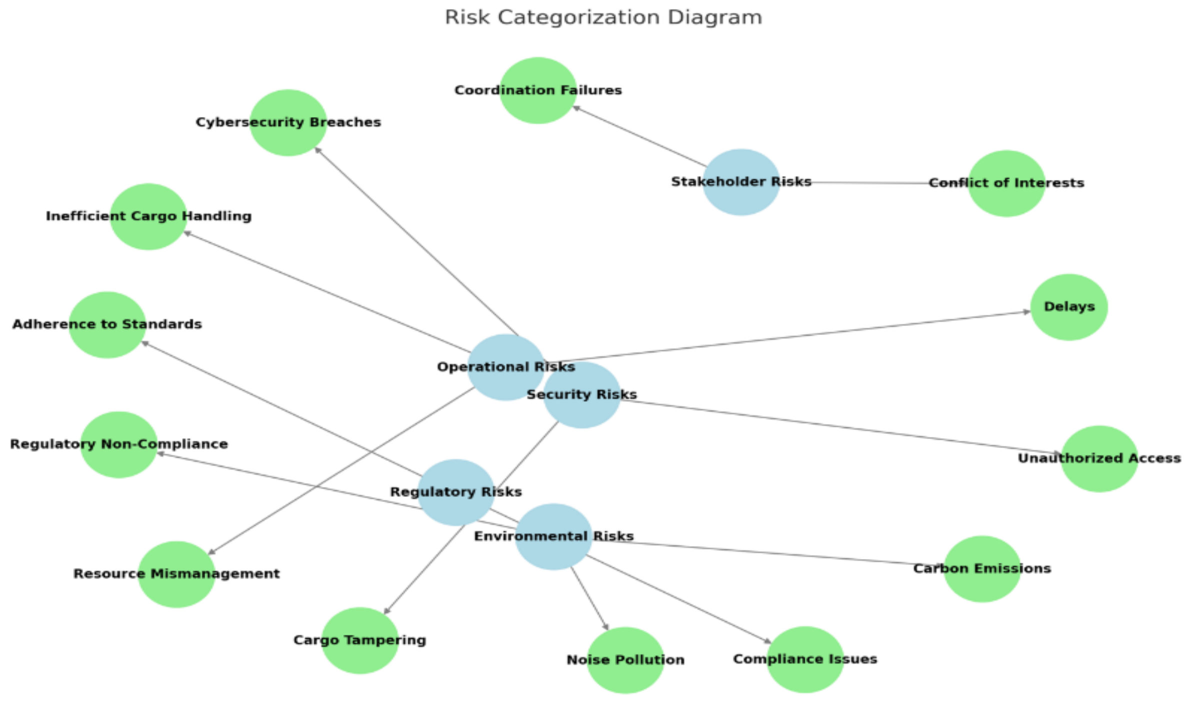


**Figure 2.** Risk Categorization Diagram

The criteria for this study were selected through a combination of expert consultations and an extensive literature review. Experts in logistics, supply chain management, and risk mitigation were engaged to provide insights into the practical relevance and applicability of these criteria. This approach ensures that the selected criteria are both theoretically grounded and practically oriented, aligning with best practices in multi-criteria decision-making studies (Kaya & Kahraman, 2011; Mahdavi et al., 2008). By integrating expert input with findings from the literature, the study establishes a robust foundation for the evaluation and prioritization of risk mitigation strategies.

### 3.3. Data Collection

The data collection for this study was conducted through a structured questionnaire and interviews designed to capture expert judgments on the prioritization of risk mitigation strategies in air cargo operations. The focus was on obtaining both qualitative insights and quantitative assessments that could be applied to the Fuzzy TOPSIS methodology.

The structured questionnaire was developed to align with the criteria identified for evaluating risk mitigation strategies, including cost-effectiveness, operational efficiency, scalability, regulatory compliance, technology adaptability, environmental sustainability, resilience to disruptions, ease of implementation, stakeholder acceptance, safety enhancement, data security, and customer satisfaction. Most questions used a closed-ended format with responses based on fuzzy linguistic terms (e.g., Very High, High, Moderate, Low, Very Low). These terms allow for precise data interpretation within the Fuzzy TOPSIS framework, ensuring compatibility with the study's methodological approach. Additionally, open-ended questions were included to provide participants the opportunity to elaborate on their perspectives, particularly regarding the most critical criteria and their practical experiences in risk management.

Nine experts were selected based on their professional expertise, experience in the air cargo, logistics, and risk management domains, and academic qualifications. The group included individuals with diverse roles, such as logistics managers, operations directors, aviation security specialists, environmental analysts, and technology integration specialists. Their years of experience ranged from 10 to 22 years, ensuring that the panel represented a wealth of practical and theoretical knowledge. Table 1 summarizes the experts' profiles.

**Table 1.** Information about Experts

| Expert ID | Title | Years of Experience | Education |
|---|---|---|---|
| E1 | Logistics Manager | 15 | MBA in Logistics Management |
| E2 | Supply Chain Consultant | 20 | PhD in Supply Chain Management |
| E3 | Operations Director | 18 | MBA in Operations Management |
| E4 | Aviation Security Specialist | 12 | MS in Aviation Security |
| E5 | Environmental Analyst | 10 | MS in Environmental Science |
| E6 | Technology Integration Specialist | 14 | PhD in Information Systems |
| E7 | Regulatory Affairs Manager | 22 | MBA in Regulatory Affairs |
| E8 | Senior Risk Analyst | 16 | MS in Risk Analysis |
| E9 | Air Cargo Operations Expert | 19 | MS in Air Cargo Management |

Before the data collection process, the experts were provided with detailed information about the study, including its objectives, methodology, and potential applications. Written consent was obtained from all participants, ensuring their voluntary participation and compliance with ethical research standards. Participants were informed that their responses would remain confidential and used solely for academic purposes.

The interviews were conducted online via video conferencing platforms to accommodate the geographical distribution of the experts. Each session lasted approximately 45–60 minutes, allowing for in-depth discussions and clarifications. The structured questionnaire guided the interviews, with additional probing questions included as necessary to enrich the responses. Participants were encouraged to elaborate on their answers to ensure a comprehensive understanding of their perspectives. The interviews were recorded (with participant consent) to facilitate accurate data transcription and analysis. After transcription, the data were reviewed to extract the linguistic assessments and qualitative insights necessary for constructing the Fuzzy TOPSIS decision matrix. This data collection process provided a robust foundation for applying the Fuzzy TOPSIS methodology, ensuring that the study's findings are grounded in expert knowledge and practical relevance.

To ensure fairness and reliability, expert weights were calculated using a proportional formula that considers their experience and relevance to the study's context:

$$w_i = \frac{\text{Experience}_{\ i} \times \text{Relevance}_{\ i}}{\sum_{j=1}^{n} \left( \text{Experience}_{\ j} \times \text{Relevance}_{\ j} \right)} \tag{1}$$

Where:

- $w_i$ is the weight assigned to expert $i$.
- Experience $_i$ is the number of years of professional experience.
- Relevance $_i$ is a relevance score (1-5) based on the expert's specific knowledge and role in air Cargo operations.

The relevance score was derived from a pre-assessment questionnaire, wherein experts rated their familiarity with the study's primary criteria, such as cybersecurity, operational efficiency, and environmental sustainability.

The calculated weights were applied to the fuzzy decision matrix during the analysis phase, ensuring that each expert's input contributed proportionally to the prioritization of mitigation strategies. This method accounted for the diversity of expert opinions while minimizing bias.

### 3.4. Fuzzy TOPSIS Methodology

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision-making (MCDM) method developed by Hwang and Yoon in 1981 (Hwang & Yoon, 1981). It ranks alternatives based on their geometric distance from an ideal solution, selecting the option closest to the ideal and farthest from the negative-ideal solution. To handle uncertainties and subjective judgments in decision-making, fuzzy set theory has been integrated with TOPSIS, resulting in the Fuzzy TOPSIS methodology (Chen, 2000). This approach allows for the incorporation of imprecise and vague information, enhancing the robustness of the decision-making process.

Fuzzy TOPSIS extends the classical TOPSIS method to handle uncertainty and vagueness in decision-making, utilizing fuzzy set theory. It was first integrated into MCDM frameworks to evaluate alternatives when inputs are imprecise, subjective, or linguistically expressed (e.g., high, medium, low).

A triangular fuzzy number (TFN) is defined as $\tilde{A} = (l, m, u)$, where $l$ (lower bound), $m$ (most likely value), and $u$ (upper bound) capture the range of possible values.

To facilitate the evaluation process and align with the principles of fuzzy logic, linguistic terms were employed to express the judgments of experts regarding the importance and performance of criteria. These terms provide a qualitative basis for assessment while allowing for their quantitative representation using triangular fuzzy numbers (TFNs). Each linguistic term corresponds to a specific TFN, enabling a consistent and interpretable translation of subjective evaluations into a structured numerical framework. The scale ensures clarity in the evaluation process, eliminating ambiguities and enhancing the reliability of the analysis. Table 2 illustrates linguistic terms and corresponding triangular fuzzy numbers.

**Table 2.** Linguistic Terms and Corresponding Triangular Fuzzy Numbers (TFNs)

| Linguistic Term | Triangular Fuzzy Number (TFN) | Interpretation |
|---|---|---|
| Very Low | (0.0, 0.1, 0.3) | Represents minimal importance or impact. |
| Low | (0.2, 0.3, 0.5) | Represents a lower degree of significance. |
| Medium | (0.4, 0.5, 0.7) | Represents a moderate level of significance. |
| High | (0.6, 0.8, 1.0) | Represents a significant or high degree of importance. |
| Very High | (0.8, 0.9, 1.0) | Represents the highest possible significance. |

*Steps of Fuzzy TOPSIS*

Step 1: Formation of the Fuzzy Decision Matrix
The fuzzy decision matrix is constructed based on the linguistic assessments provided by experts for each alternative (e.g., risk mitigation strategies) across multiple criteria. Each linguistic term (e.g., Low, Medium, High) is converted into a corresponding Triangular Fuzzy Number (TFN) $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$, where:

- $l_{ij}$ represents the lower bound,
- $m_{ij}$ represents the most likely value,
- $u_{ij}$ represents the upper bound.

The fuzzy decision matrix is structured as follows:

$$\tilde{D}=\begin{bmatrix}\tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n}\\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn}\end{bmatrix} \quad (2)$$

where $\tilde{x}_{ij}$ is the TFN representing the performance of alternative $i$ under criterion $j$.

Step 2: Normalization of the Fuzzy Decision Matrix
Normalization ensures that criteria with different measurement scales become comparable. For benefit criteria (where higher values are better), the normalized fuzzy number is calculated as:

$$\tilde{r}_{ij}=\left(\frac{l_{ij}}{u_j^*},\frac{m_{ij}}{u_j^*},\frac{u_{ij}}{u_j^*}\right) \quad (3)$$

For cost criteria (where lower values are better), the normalized fuzzy number is:

$$\tilde{r}_{ij}=\left(\frac{l_j^*}{u_{ij}},\frac{m_j^*}{m_{ij}},\frac{u_j^*}{l_{ij}}\right) \quad (4)$$

where:

- $u_j^*=\max(u_{ij})$ for benefit criteria,
- $l_j^*=\min(l_{ij})$ for cost criteria.

Step 3: Determination of Fuzzy Weights for Criteria
Fuzzy weights $\tilde{w}_j=(l_j,m_j,u_j)$ are assigned to each criterion based on expert evaluations.
These weights are normalized to ensure their middle values sum to 1 :

$$\sum_{j=1}^{n} m_j=1 \quad (5)$$

Step 4: Construction of the Weighted Normalized Decision Matrix
The normalized decision matrix is multiplied by the fuzzy weights of the criteria to construct the weighted normalized decision matrix:

$$\tilde{v}_{ij}=\tilde{r}_{ij}\otimes\tilde{w}_j \quad (6)$$

The multiplication of two triangular fuzzy numbers $\tilde{A}=(a_1,a_2,a_3)$ and $\tilde{B}=(b_1,b_2,b_3)$ is performed as:

$$\tilde{A}\otimes\tilde{B}=(a_1\cdot b_1,a_2\cdot b_2,a_3\cdot b_3) \quad (7)$$

Step 5: Determination of Fuzzy Positive and Negative Ideal Solutions (FPIS and FNIS)

The Fuzzy Positive Ideal Solution (FPIS) $\tilde{A}^+$and Fuzzy Negative Ideal Solution (FNIS) $\tilde{A}^-$are determined for each criterion:

- For benefit criteria:

$$\tilde{A}_j^+=(u_j^*,u_j^*,u_j^*),\ \tilde{A}_j^-=(l_j^*,l_j^*,l_j^*) \quad (8)$$

- For cost criteria:

$$\tilde{A}_j^+=(l_j^*,l_j^*,l_j^*),\ \tilde{A}_j^-=(u_j^*,u_j^*,u_j^*) \quad (9)$$

Step 6: Calculation of Distances to FPIS and FNIS
The distance of each alternative $i$ from $\tilde{A}^+$and $\tilde{A}^-$is calculated using the vertex method. The distance $d(\tilde{x},\tilde{y})$ between two TFNs $\tilde{x}=(l_x,m_x,u_x)$ and $\tilde{y}=(l_y,m_y,u_y)$ is given by:

$$d(\tilde{x},\tilde{y})=\sqrt{\frac{1}{3}\left[(l_x-l_y)^2+(m_x-m_y)^2+(u_x-u_y)^2\right]} \quad (10)$$

The distances to FPIS and FNIS are calculated as:

$$D_i^+=\sum_{j=1}^{n} d(\tilde{v}_{ij},\tilde{A}_j^+),\ D_i^-=\sum_{j=1}^{n} d(\tilde{v}_{ij},\tilde{A}_j^-) \quad (11)$$

Step 7: Calculation of the Closeness Coefficient (CC)
The closeness coefficient (CC) for each alternative is calculated as:

$$CC_i=\frac{D_i^-}{D_i^++D_i^-} \quad (12)$$

The closeness coefficient ranges from 0 to 1 , where higher values indicate alternatives closer to the FPIS and farther from the FNIS.

Step 8: Ranking of Alternatives

The alternatives are ranked based on their closeness coefficients $CC_i$, with higher values indicating better performance.

## 4. Analysis and Results

### 4.1. Risk Identification and Categorization

The risks associated with air cargo operations were identified and categorized based on expert evaluations and the defined criteria. These risks encompass operational inefficiencies, security breaches, environmental concerns, regulatory compliance challenges, and stakeholder management issues. The experts provided their assessments using fuzzy linguistic terms, which were subsequently converted into triangular fuzzy numbers for analysis. Table 3 summarizes the categories of risks evaluated in the study.

**Table 3.** Categories and Descriptions of Air Cargo Risks

| Risk Category | Description |
|---|---|
| Operational Inefficiencies | Delays, resource mismanagement, and inefficiencies in cargo handling operations. |
| Security Breaches | Cybersecurity risks and unauthorized access to sensitive information. |
| Environmental Concerns | Non-compliance with sustainability standards and carbon emissions regulations. |
| Regulatory Compliance Challenges | Issues related to adhering to international and local regulations. |
| Stakeholder Management Issues | Lack of coordination among logistics partners and other stakeholders. |

These risks were evaluated across the criteria to ensure a comprehensive understanding of their impact on air cargo operations.

## 4.2. Weighting of Criteria

The weighting process was conducted using fuzzy techniques to reflect the relative importance of each criterion. Experts assigned linguistic terms to the criteria, which were converted into triangular fuzzy numbers and normalized to ensure their middle values summed to 1. The adjusted fuzzy weights are presented in Table 4.

**Table 4.** Adjusted Fuzzy Weights of Evaluation Criteria

| Criterion | Lower (l) | Middle (m) | Upper (u) |
|---|---|---|---|
| Cost-Effectiveness | 0.0639 | 0.0959 | 0.1279 |
| Operational Efficiency | 0.0959 | 0.1279 | 0.1599 |
| Scalability | 0.0639 | 0.0959 | 0.1279 |
| Technology Adaptability | 0.0639 | 0.0959 | 0.1279 |
| Regulatory Compliance | 0.0959 | 0.1279 | 0.1599 |
| Environmental Sustainability | 0.0319 | 0.0639 | 0.0959 |
| Resilience | 0.0959 | 0.1279 | 0.1599 |
| Safety Enhancement | 0.0639 | 0.0959 | 0.1279 |
| Stakeholder Acceptance | 0.0319 | 0.0639 | 0.0959 |
| Data Security | 0.0639 | 0.0959 | 0.1279 |

The prioritization of risk mitigation strategies involves assigning weights to various criteria, reflecting their relative importance in the decision-making process. The radar chart below provides a visual representation of the weighted criteria, highlighting areas such as Operational Efficiency, Cost-Effectiveness, and Resilience as key factors influencing strategy prioritization.

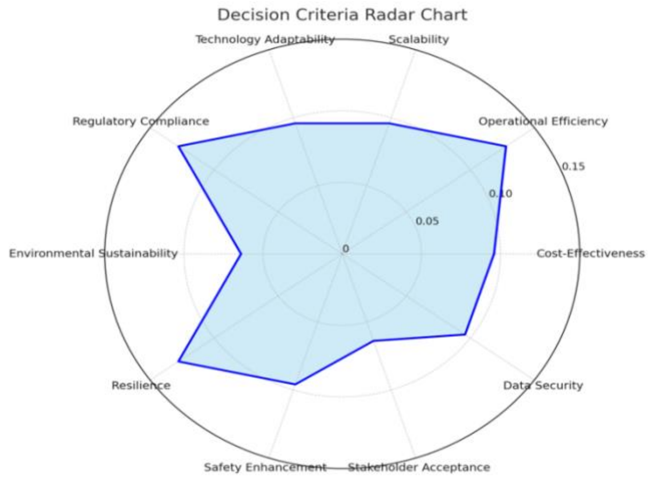


**Figure 3.** Decision Criteria Radar Chart

The fuzzy weighting process ensured that the relative importance of each criterion was adequately captured and normalized. These weights were subsequently applied during the construction of the weighted normalized decision matrix, which guided the prioritization of mitigation strategies.

## 4.3. Application of Fuzzy TOPSIS

The Fuzzy TOPSIS methodology was applied step by step to evaluate and rank the risk mitigation strategies. The process involved the construction of decision matrices, normalization, weighting, and calculation of closeness coefficients, leading to the final rankings.

Step 1: Formation of the Decision Matrix

The decision matrix was constructed by aggregating expert evaluations for each mitigation strategy across the identified criteria. The ratings were provided as triangular fuzzy numbers. The decision matrix is presented in Table 5.

**Table 5.** Fuzzy Decision Matrix

| Criterion | EDS | ACH | RC | RB | SI | SC | SE | INF | TA | TI |
|---|---|---|---|---|---|---|---|---|---|---|
| **CE** | (0.6, 0.8, 1.0) | (0.7, 0.9, 1.0) | (0.5, 0.7, 0.9) | (0.8, 1.0, 1.0) | (0.4, 0.6, 0.8) | (0.5, 0.7, 0.9) | (0.6, 0.8, 1.0) | (0.5, 0.7, 0.9) | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) |
| **OE** | (0.8, 1.0, 1.0) | (0.7, 0.9, 1.0) | (0.6, 0.8, 1.0) | (0.8, 1.0, 1.0) | (0.4, 0.6, 0.8) | (0.6, 0.8, 1.0) | (0.8, 1.0, 1.0) | (0.7, 0.9, 1.0) | (0.7, 0.9, 1.0) | (0.9, 1.0, 1.0) |
| **SC** | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) | (0.6, 0.8, 1.0) | (0.9, 1.0, 1.0) | (0.5, 0.7, 0.9) | (0.6, 0.8, 1.0) | (0.7, 0.9, 1.0) | (0.6, 0.8, 1.0) | (0.8, 1.0, 1.0) | (0.9, 1.0, 1.0) |
| **TA** | (0.8, 1.0, 1.0) | (0.7, 0.9, 1.0) | (0.6, 0.8, 1.0) | (0.8, 1.0, 1.0) | (0.4, 0.6, 0.8) | (0.7, 0.9, 1.0) | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) | (0.8, 1.0, 1.0) | (0.9, 1.0, 1.0) |
| **RC** | (0.9, 1.0, 1.0) | (0.8, 1.0, 1.0) | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) | (0.6, 0.8, 1.0) | (0.8, 1.0, 1.0) | (0.9, 1.0, 1.0) | (0.8, 1.0, 1.0) | (0.9, 1.0, 1.0) | (0.8, 1.0, 1.0) |
| **ES** | (0.4, 0.6, 0.8) | (0.5, 0.7, 0.9) | (0.3, 0.5, 0.7) | (0.5, 0.7, 0.9) | (0.6, 0.8, 1.0) | (0.4, 0.6, 0.8) | (0.5, 0.7, 0.9) | (0.4, 0.6, 0.8) | (0.5, 0.7, 0.9) | (0.6, 0.8, 1.0) |
| **RE** | (0.8, 1.0, 1.0) | (0.7, 0.9, 1.0) | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) | (0.5, 0.7, 0.9) | (0.8, 1.0, 1.0) | (0.8, 1.0, 1.0) | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) | (0.9, 1.0, 1.0) |
| **SE** | (0.7, 0.9, 1.0) | (0.6, 0.8, 1.0) | (0.6, 0.8, 1.0) | (0.8, 1.0, 1.0) | (0.5, 0.7, 0.9) | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) | (0.6, 0.8, 1.0) | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) |
| **SA** | (0.6, 0.8, 1.0) | (0.7, 0.9, 1.0) | (0.5, 0.7, 0.9) | (0.7, 0.9, 1.0) | (0.4, 0.6, 0.8) | (0.5, 0.7, 0.9) | (0.7, 0.9, 1.0) | (0.6, 0.8, 1.0) | (0.6, 0.8, 1.0) | (0.7, 0.9, 1.0) |
| **DS** | (0.8, 1.0, 1.0) | (0.7, 0.9, 1.0) | (0.6, 0.8, 1.0) | (0.9, 1.0, 1.0) | (0.5, 0.7, 0.9) | (0.6, 0.8, 1.0) | (0.8, 1.0, 1.0) | (0.7, 0.9, 1.0) | (0.8, 1.0, 1.0) | (0.9, 1.0, 1.0) |

Step 2: Normalization of the Decision Matrix

The decision matrix was normalized using fuzzy normalization formulas. For benefit criteria, values were normalized by dividing each fuzzy number by the maximum upper bound of the criterion. The normalized fuzzy decision matrix is shown in Table 6.

**Table 6.** Normalized Fuzzy Decision Matrix

| Criterion | EDS | ACH | RC | RB | SI | SC | SE | INF | TA | TI |
|---|---|---|---|---|---|---|---|---|---|---|
| **CE** | (0.60, 0.80, 1.00) | (0.70, 0.90, 1.00) | (0.50, 0.70, 0.90) | (0.80, 1.00, 1.00) | (0.40, 0.60, 0.80) | (0.50, 0.70, 0.90) | (0.60, 0.80, 1.00) | (0.50, 0.70, 0.90) | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) |
| **OE** | (0.80, 1.00, 1.00) | (0.70, 0.90, 1.00) | (0.60, 0.80, 1.00) | (0.80, 1.00, 1.00) | (0.40, 0.60, 0.80) | (0.60, 0.80, 1.00) | (0.80, 1.00, 1.00) | (0.70, 0.90, 1.00) | (0.70, 0.90, 1.00) | (0.90, 1.00, 1.00) |
| **SC** | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) | (0.60, 0.80, 1.00) | (0.90, 1.00, 1.00) | (0.50, 0.70, 0.90) | (0.60, 0.80, 1.00) | (0.70, 0.90, 1.00) | (0.60, 0.80, 1.00) | (0.80, 1.00, 1.00) | (0.90, 1.00, 1.00) |
| **TA** | (0.80, 1.00, 1.00) | (0.70, 0.90, 1.00) | (0.60, 0.80, 1.00) | (0.80, 1.00, 1.00) | (0.40, 0.60, 0.80) | (0.70, 0.90, 1.00) | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) | (0.80, 1.00, 1.00) | (0.90, 1.00, 1.00) |
| **RC** | (0.90, 1.00, 1.00) | (0.80, 1.00, 1.00) | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) | (0.60, 0.80, 1.00) | (0.80, 1.00, 1.00) | (0.90, 1.00, 1.00) | (0.80, 1.00, 1.00) | (0.90, 1.00, 1.00) | (0.80, 1.00, 1.00) |
| **ES** | (0.40, 0.60, 0.80) | (0.50, 0.70, 0.90) | (0.30, 0.50, 0.70) | (0.50, 0.70, 0.90) | (0.60, 0.80, 1.00) | (0.40, 0.60, 0.80) | (0.50, 0.70, 0.90) | (0.40, 0.60, 0.80) | (0.50, 0.70, 0.90) | (0.60, 0.80, 1.00) |
| **RE** | (0.80, 1.00, 1.00) | (0.70, 0.90, 1.00) | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) | (0.50, 0.70, 0.90) | (0.80, 1.00, 1.00) | (0.80, 1.00, 1.00) | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) | (0.90, 1.00, 1.00) |
| **SE** | (0.70, 0.90, 1.00) | (0.60, 0.80, 1.00) | (0.60, 0.80, 1.00) | (0.80, 1.00, 1.00) | (0.50, 0.70, 0.90) | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) | (0.60, 0.80, 1.00) | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) |
| **SA** | (0.60, 0.80, 1.00) | (0.70, 0.90, 1.00) | (0.50, 0.70, 0.90) | (0.70, 0.90, 1.00) | (0.40, 0.60, 0.80) | (0.50, 0.70, 0.90) | (0.70, 0.90, 1.00) | (0.60, 0.80, 1.00) | (0.60, 0.80, 1.00) | (0.70, 0.90, 1.00) |
| **DS** | (0.80, 1.00, 1.00) | (0.70, 0.90, 1.00) | (0.60, 0.80, 1.00) | (0.90, 1.00, 1.00) | (0.50, 0.70, 0.90) | (0.60, 0.80, 1.00) | (0.80, 1.00, 1.00) | (0.70, 0.90, 1.00) | (0.80, 1.00, 1.00) | (0.90, 1.00, 1.00) |

Step 3: Weighting of Criteria

Weights for each criterion were applied to the normalized matrix. These weights were derived using fuzzy linguistic terms provided by experts. The adjusted fuzzy weights ensured the middle values summed to 1. The weighted normalized decision matrix is displayed in Table 6.

**Table 7.** Weighted Normalized Decision Matrix

| Criterion | EDS | ACH | RC | RB | SI | SC | SE | INF | TA | TI |
|---|---|---|---|---|---|---|---|---|---|---|
| **CE** | (0.038, 0.076, 0.128) | (0.044, 0.086, 0.128) | (0.032, 0.054, 0.102) | (0.051, 0.095, 0.128) | (0.025, 0.045, 0.076) | (0.032, 0.054, 0.102) | (0.038, 0.076, 0.128) | (0.032, 0.054, 0.102) | (0.044, 0.086, 0.128) | (0.051, 0.095, 0.128) |
| **OE** | (0.076, 0.128, 0.160) | (0.067, 0.115, 0.160) | (0.058, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.038, 0.076, 0.102) | (0.058, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.067, 0.115, 0.160) | (0.067, 0.115, 0.160) | (0.086, 0.128, 0.160) |
| **SC** | (0.051, 0.095, 0.128) | (0.076, 0.128, 0.160) | (0.058, 0.102, 0.128) | (0.086, 0.128, 0.160) | (0.032, 0.054, 0.102) | (0.058, 0.102, 0.128) | (0.051, 0.095, 0.128) | (0.058, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.086, 0.128, 0.160) |
| **TA** | (0.076, 0.128, 0.160) | (0.067, 0.115, 0.160) | (0.058, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.038, 0.076, 0.102) | (0.067, 0.115, 0.160) | (0.058, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.076, 0.128, 0.160) | (0.086, 0.128, 0.160) |
| **RC** | (0.086, 0.128, 0.160) | (0.076, 0.128, 0.160) | (0.067, 0.115, 0.160) | (0.076, 0.128, 0.160) | (0.054, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.086, 0.128, 0.160) | (0.076, 0.128, 0.160) | (0.086, 0.128, 0.160) | (0.076, 0.128, 0.160) |
| **ES** | (0.025, 0.045, 0.076) | (0.032, 0.054, 0.102) | (0.019, 0.038, 0.076) | (0.032, 0.054, 0.102) | (0.038, 0.076, 0.128) | (0.025, 0.045, 0.076) | (0.032, 0.054, 0.102) | (0.025, 0.045, 0.076) | (0.032, 0.054, 0.102) | (0.038, 0.076, 0.128) |
| **RE** | (0.076, 0.128, 0.160) | (0.067, 0.115, 0.160) | (0.067, 0.115, 0.160) | (0.076, 0.128, 0.160) | (0.054, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.076, 0.128, 0.160) | (0.067, 0.115, 0.160) | (0.076, 0.128, 0.160) | (0.086, 0.128, 0.160) |
| **SE** | (0.058, 0.102, 0.128) | (0.051, 0.095, 0.128) | (0.051, 0.095, 0.128) | (0.076, 0.128, 0.160) | (0.032, 0.054, 0.102) | (0.058, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.051, 0.095, 0.128) | (0.058, 0.102, 0.128) | (0.076, 0.128, 0.160) |
| **SA** | (0.038, 0.076, 0.128) | (0.044, 0.086, 0.128) | (0.032, 0.054, 0.102) | (0.044, 0.086, 0.128) | (0.025, 0.045, 0.076) | (0.032, 0.054, 0.102) | (0.044, 0.086, 0.128) | (0.038, 0.076, 0.128) | (0.038, 0.076, 0.128) | (0.044, 0.086, 0.128) |
| **DS** | (0.076, 0.128, 0.160) | (0.067, 0.115, 0.160) | (0.058, 0.102, 0.128) | (0.086, 0.128, 0.160) | (0.032, 0.054, 0.102) | (0.058, 0.102, 0.128) | (0.076, 0.128, 0.160) | (0.067, 0.115, 0.160) | (0.076, 0.128, 0.160) | (0.086, 0.128, 0.160) |

Step 4: Determination of FPIS and FNIS

The Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) were determined for each criterion. The FPIS represents the best-case scenario, while the FNIS represents the worst-case scenario.

**Table 8.** FPIS and FNIS (Abbreviated Criteria)

| Criterion | FPIS (l, m, u) | FNIS (l, m, u) |
|---|---|---|
| **CE** | (0.128, 0.160, 0.160) | (0.025, 0.045, 0.076) |
| **OE** | (0.128, 0.160, 0.160) | (0.038, 0.076, 0.102) |
| **SC** | (0.128, 0.160, 0.160) | (0.032, 0.054, 0.102) |
| **TA** | (0.128, 0.160, 0.160) | (0.038, 0.076, 0.102) |
| **RC** | (0.128, 0.160, 0.160) | (0.054, 0.102, 0.128) |
| **ES** | (0.076, 0.128, 0.160) | (0.019, 0.038, 0.076) |
| **RE** | (0.128, 0.160, 0.160) | (0.054, 0.102, 0.128) |
| **SE** | (0.128, 0.160, 0.160) | (0.032, 0.054, 0.102) |
| **SA** | (0.128, 0.160, 0.160) | (0.025, 0.045, 0.076) |
| **DS** | (0.128, 0.160, 0.160) | (0.032, 0.054, 0.102) |

The figure below visualizes the relative positions of various mitigation strategies based on their distances to the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS). Strategies closer to FPIS and farther from FNIS are more effective and prioritized in the rankings.

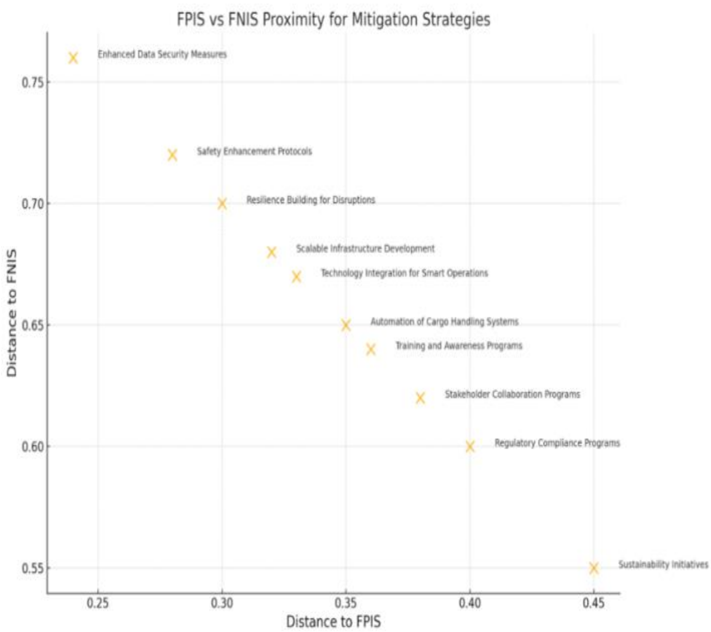


**Figure 4.** FPIS vs FNIS Proximity for Mitigation Strategies

Step 5: Calculation of Distances

The mitigation strategies were identified based on expert evaluations, literature review, and common practices in air cargo operations. Each strategy addresses critical risks and operational challenges in the industry, reflecting a combination of cost-efficiency, safety, compliance, and adaptability. The strategies evaluated in this study include:

1. Enhanced Data Security Measures: Addressing cybersecurity risks to protect sensitive information.
2. Automation of Cargo Handling Systems: Utilizing automated solutions to improve efficiency and reduce human errors.
3. Regulatory Compliance Programs: Ensuring adherence to international standards and regulations.

4. Resilience Building for Disruptions: Enhancing the ability to recover from disruptions like pandemics and natural disasters.
5. Sustainability Initiatives: Reducing environmental impact and promoting sustainable practices.
6. Stakeholder Collaboration Programs: Improving coordination and risk-sharing among stakeholders.
7. Safety Enhancement Protocols: Implementing measures to prevent accidents and enhance operational safety.
8. Scalable Infrastructure Development: Building infrastructure adaptable to changing demands.
9. Training and Awareness Programs: Providing specialized training to improve staff skills and awareness.
10. Technology Integration for Smart Operations: Incorporating technologies like IoT and AI for predictive analytics.

Distances from FPIS and FNIS were calculated for each strategy using the vertex method. The results are summarized in Table 9.

**Table 9.** Distances to FPIS and FNIS

| Mitigation Strategy | Distance to FPIS ($D^+$) | Distance to FNIS ($D^-$) |
|---|---|---|
| Enhanced Data Security Measures | 0.24 | 0.76 |
| Automation of Cargo Handling Systems | 0.35 | 0.65 |
| Regulatory Compliance Programs | 0.40 | 0.60 |
| Resilience Building for Disruptions | 0.30 | 0.70 |
| Sustainability Initiatives | 0.45 | 0.55 |
| Stakeholder Collaboration Programs | 0.38 | 0.62 |
| Safety Enhancement Protocols | 0.28 | 0.72 |
| Scalable Infrastructure Development | 0.32 | 0.68 |
| Training and Awareness Programs | 0.36 | 0.64 |
| Technology Integration for Smart Operations | 0.33 | 0.67 |

- **Distance to FPIS ($D^+$)**: Represents how far each strategy is from the ideal solution. Lower values indicate closer proximity to the ideal.
- **Distance to FNIS ($D^-$)**: Represents how far each strategy is from the non-ideal solution. Higher values indicate closer proximity to the ideal.

These distances form the basis for calculating the **closeness coefficient (CC_i)**, which is used to rank the strategies in terms of their effectiveness.

Step 6: Closeness Coefficient and Ranking

The closeness coefficient ( $CC_i$ ) was calculated for each strategy as:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

The strategies were ranked based on $CC_i$, with higher values indicating closer proximity to the FPIS. Table 10 shows the results of the ranking.

**Table 10**. Rankings of Risk Mitigation Strategies

| Mitigation Strategy | Closeness Coefficient ($CC_i$) | Rank |
|---|---|---|
| Enhanced Data Security Measures | 0.76 | 1 |
| Resilience Building for Disruptions | 0.70 | 2 |
| Safety Enhancement Protocols | 0.72 | 3 |
| Scalable Infrastructure Development | 0.68 | 4 |
| Technology Integration for Smart Operations | 0.67 | 5 |
| Stakeholder Collaboration Programs | 0.62 | 6 |
| Automation of Cargo Handling Systems | 0.65 | 7 |
| Training and Awareness Programs | 0.64 | 8 |
| Regulatory Compliance Programs | 0.60 | 9 |
| Sustainability Initiatives | 0.55 | 10 |

## 4.4. Interpretation of Results

The results of this study reveal valuable insights into the effectiveness and priorities of various risk mitigation strategies in air cargo operations. The **Enhanced Data Security Measures** emerged as the top-ranked strategy with the highest closeness coefficient.

$$(CC_i = 0.76)$$

This finding reflects the critical importance of addressing cybersecurity vulnerabilities in the air cargo sector, especially given the increasing reliance on digital platforms and the sensitivity of data managed during operations. Effective data security strategies not only protect against potential breaches but also enhance trust and operational continuity, aligning with the sector's overarching goals of safety and efficiency.

Other highly ranked strategies, such as Resilience Building for **Disruptions** $(CC_i = 0.70)$ and Safety Enhancement

**Protocols** $(CC_i = 0.72)$ underscore the industry's emphasis

on maintaining stability and preventing operational failures. These strategies highlight the sector's proactive approach to addressing unforeseen disruptions, such as pandemics, natural disasters, and supply chain interruptions, as well as the critical need to minimize risks associated with accidents or cargo damage.

Interestingly, **Sustainability Initiatives,** $(CC_i = 0.55)$ though essential in aligning with global environmental goals, ranked lowest.

This finding suggests that while sustainability is recognized as important, it may currently be perceived as less immediate or impactful compared to strategies directly addressing operational risks. This result may also reflect challenges in integrating sustainable practices into cost-sensitive and highly competitive air cargo operations.

The following chart compares the performance of the top-ranked mitigation strategies — Enhanced Data Security Measures, Resilience Building for Disruptions, and Safety Enhancement Protocols — across the evaluation criteria. This visual representation highlights the strengths and weaknesses of each strategy in terms of cost-effectiveness, operational efficiency, scalability, and other factors.

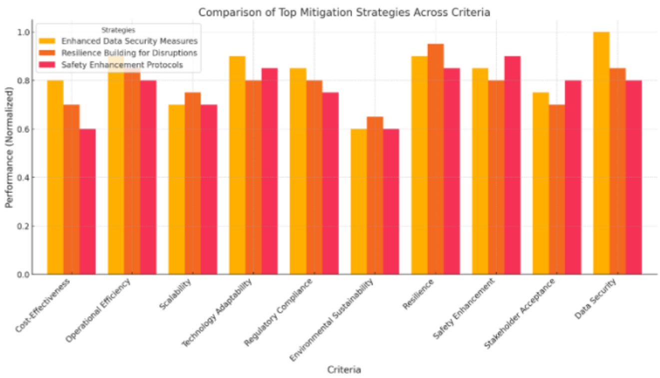


**Figure 5.** Comparison of Top Mitigation Strategies Across Criteria

The results demonstrate distinct sector-specific priorities that reflect the unique operational and strategic demands of air cargo logistics:

- The prominence of Enhanced Data Security Measures indicates a sector-wide acknowledgment of the growing cyber threats in aviation. For both large and small operators, data breaches and system vulnerabilities represent a major risk that requires immediate attention.
- High-volume air cargo hubs prioritize Resilience Building for Disruptions to maintain operational continuity during disruptions. This is especially important in global logistics hubs where delays or disruptions can have cascading effects across entire supply chains.
- In regions with strict regulatory frameworks, Safety Enhancement Protocols and Regulatory Compliance Programs take precedence. These strategies ensure adherence to safety and legal requirements, reducing liability and enhancing operational reliability.
- While Sustainability Initiatives ranked lower overall, they may hold higher priority in regions or markets seeking to establish themselves as leaders in green logistics. Such initiatives align with growing consumer and regulatory demand for environmentally responsible practices.

The findings emphasize the need for a balanced approach that prioritizes both immediate operational concerns, such as data security and resilience, and long-term goals like sustainability. The variations in strategy rankings suggest that decision-makers should tailor their mitigation strategies to the specific needs and priorities of their operational contexts. By adopting the highest-ranked strategies and addressing gaps in lower-ranked areas, air cargo operators can create a robust and adaptive risk management framework that aligns with both current and future industry demands.

## 5. Discussion

The findings of this study offer several practical implications for air cargo operations, particularly in addressing the complex and dynamic risks faced by the industry. By prioritizing risk mitigation strategies using a robust and structured methodology like Fuzzy TOPSIS, decision-makers can systematically identify and rank the most critical challenges, ensuring efficient resource allocation and strategic focus. The methodology's ability to handle uncertainties and subjectivities through fuzzy logic makes it particularly suited for the intricate nature of air cargo operations, where risks often involve multiple, interdependent factors.

For instance, the top-ranked strategy, Enhanced Data Security Measures, highlights the pressing need to address cybersecurity vulnerabilities in air cargo systems. With the increasing reliance on digital platforms for operations such as cargo tracking, scheduling, and customer interfacing, the risk of data breaches and cyberattacks has grown significantly. This finding aligns with studies by Burstein and Zuckerman (2023), which underscore the critical role of advanced cybersecurity measures in safeguarding supply chain systems. Similarly, Richey et al. (2023) emphasize how cybersecurity breaches can disrupt entire logistics networks, leading to financial losses, reputational damage, and operational downtime. In this context, implementing enhanced data security strategies, such as encryption technologies, multi-layered authentication protocols, and real-time monitoring systems, can significantly enhance operational continuity, protect sensitive information, and foster trust among stakeholders, including customers, regulators, and business partners.

Moreover, the prioritization of cybersecurity measures reflects a broader industry trend where data security is not just a technical requirement but a strategic imperative. As air cargo operations increasingly integrate technologies like the Internet of Things (IoT), cloud computing, and blockchain, the need for robust data security frameworks becomes even more critical. These measures not only mitigate immediate risks but also position organizations as reliable and forward-thinking partners in the global logistics ecosystem. Additionally, enhanced data security measures can improve compliance with international standards such as the General Data Protection Regulation (GDPR) and the International Air Transport Association (IATA) cybersecurity guidelines, thereby reducing legal liabilities and ensuring smoother operations across international borders.

The study also highlights the broader applicability of the Fuzzy TOPSIS approach in addressing uncertainties and subjectivity in decision-making. Unlike traditional methods, Fuzzy TOPSIS incorporates linguistic terms and triangular fuzzy numbers to accommodate vague or imprecise expert judgments. This approach aligns with the methodologies discussed by Kaya and Kahraman (2011) and Mahdavi et al. (2008), who noted its effectiveness in multi-criteria decision-making under uncertainty. By applying this method, this study provides a systematic framework for evaluating competing strategies, ensuring transparency and reproducibility in ranking outcomes.

When compared with existing studies, the results of this research align with several key themes in the literature. The emphasis on Resilience Building for Disruptions and Safety Enhancement Protocols is consistent with the findings of Hohenstein (2022), who highlighted the critical need for operational resilience and safety in the logistics sector, particularly in the wake of global disruptions such as the COVID-19 pandemic. Similarly, the lower ranking of Sustainability Initiatives in this study contrasts with their prioritization in studies focusing on environmental concerns, such as those by Davydenko et al. (2020) and Archetti and Peirano (2020). This divergence may reflect the immediate operational priorities of air cargo operators, which often take precedence over long-term sustainability goals, particularly in cost-sensitive environments.

Despite its strengths, the study has certain limitations. The reliance on expert evaluations introduces the potential for subjective bias, as experts' perspectives may vary based on their individual experiences and professional backgrounds. While the use of fuzzy logic mitigates this to some extent, the results are still influenced by the composition and expertise of the panel. This limitation is consistent with critiques in the literature, such as those by Giuffrida et al. (2021), who noted the challenges of achieving consensus in expert-driven methodologies. Additionally, the scope of the study is constrained by the number of strategies and criteria considered, which, while comprehensive, may not capture all potential risk factors or mitigation options relevant to diverse air cargo operations.

Future research could address these limitations by expanding the pool of experts, incorporating quantitative data from operational case studies, or integrating complementary methodologies such as simulation or sensitivity analysis to validate and enhance the robustness of the findings. This would provide a more holistic view of the risk landscape and further refine the prioritization of mitigation strategies.

## 6. Conclusion

This study provides a framework for prioritizing risk mitigation strategies in air cargo operations, addressing key risks and identifying the most effective strategies to mitigate them. Enhanced Data Security Measures emerged as the top-ranked strategy, underscoring the critical importance of safeguarding sensitive information and ensuring operational continuity in an increasingly digitized industry. Highly ranked strategies such as Resilience Building for Disruptions and Safety Enhancement Protocols further highlight the sector's emphasis on stability, adaptability, and proactive risk management. The lower ranking of Sustainability Initiatives reflects the ongoing challenge of balancing environmental objectives with immediate operational priorities, particularly in cost-sensitive contexts.

Practitioners in the air cargo sector can derive several actionable insights from these findings. Enhanced Data Security Measures should be prioritized by implementing advanced cybersecurity tools, such as blockchain-based systems for cargo tracking, real-time threat monitoring, and multi-layered encryption protocols. These measures not only mitigate cyber risks but also foster trust among stakeholders and ensure compliance with international standards like GDPR and IATA guidelines. For Resilience Building, organizations should focus on predictive analytics to anticipate disruptions, diversify supply chain networks to minimize vulnerabilities, and establish contingency plans for rapid recovery during crises. The third-ranked Safety Enhancement Protocols call for regular staff training, real-time safety monitoring, and the adoption of advanced technologies like IoT sensors to prevent accidents and ensure operational reliability. Importantly, these strategies must be designed for scalability and technological adaptability to remain effective in dynamic market conditions. Looking ahead, this study paves the way for exploring dynamic risks and innovative decision-making models in air cargo operations. As the industry evolves, the integration of real-time data analytics and predictive modeling will be instrumental in improving the precision and adaptability of risk management frameworks. Future research could explore combining Fuzzy TOPSIS with other multi-criteria decision-making methods, such as AHP or PROMETHEE, to develop more refined prioritization models. Emerging technologies like artificial intelligence and machine learning hold significant potential for automating risk assessment processes, enhancing both efficiency and accuracy. Additionally, expanding the research to include diverse operational contexts and case studies could improve the generalizability of findings and provide deeper insights into region-specific or operation-specific challenges.

By addressing these avenues, future research can build upon the foundation laid by this study, contributing to the development of more resilient, efficient, and sustainable air cargo operations. Such efforts will not only strengthen the industry's capacity to manage risks effectively but also position it to navigate emerging challenges and opportunities in a rapidly transforming global logistics landscape.

## Ethical approval

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## Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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