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Fatigue Risk Management in the Logistics and Aviation Sectors: A Multi-Criteria Approach

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Abstract

Employees working in the logistics and aviation sectors are heavily exposed to fatigue risks due to challenging factors such as long working hours, irregular shift systems, high workload, and intense stress. Given the high-reliability nature of these industries, fatigue is not merely a health issue but a critical threat to operational safety and service quality. In this study, a hybrid Multi-Criteria Decision-Making (MCDM) approach was adopted to identify and analyze the main factors causing fatigue risk. The causal relationships among these factors were analyzed using the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method, while their relative significance levels were evaluated with the Best-Worst Method (BWM). Eight criteria were determined based on a comprehensive literature review and expert opinions, followed by a decision-making process involving 20 industry experts. According to the DEMATEL results, "C4-Task continuity," "C6-Physiological conditions," and "C7-Level of training and awareness" emerged as the primary causal factors, indicating that improvements in these areas trigger positive effects on other variables. Meanwhile, "C1-Workload intensity" and "C2-Shift schedule and working hours" were identified as result

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This study builds upon and expands the preliminary findings presented in the paper titled "Lojistik Ve Havacilik Yönetiminde Yorgunluk Risk Yönetimi Ortak Kriterlerinin Dematel Yöntemi İle Değerlendirilmesi" (Evaluation of Common Criteria for Fatigue Risk Management in Logistics and Aviation Management using the DEMATEL Method) at the II. Havacılıkta İnsan Faktörleri Sempozyumu (2nd Symposium on Human Factors in Aviation) (October 29-30, 2025).

factors. Furthermore, the BWM results highlighted that "C5-Psychological stress level," "C2-Shift schedule and working hours," and "C1-Workload intensity" were the criteria with the highest weights. Consequently, this study provides a robust framework for practitioners to prioritize fatigue risk management strategies, thereby enhancing both employee well-being and operational safety.

Key words: Fatigue Risk Management System, DEMATEL, Best-Worst Method (BWM), Logistics, Aviation

JEL Code: L91, J81

1. Introduction

The logistics and aviation industries are fields that play critical roles in the functioning of the global economy, characterized by high operational complexity (Smith, 2018). In these sectors, operations are typically time-sensitive and conducted under intense tempo, requiring employees to maintain high levels of attention, concentration, and alertness (Jones & Brown, 2020). However, the combination of long working hours, irregular shift systems, and stress factors creates favorable conditions for the development of fatigue among employees (Lee et al., 2019).

Since the aviation industry operates on a 24/7 basis, complete elimination of fatigue is impossible, even though the human brain and body function best with uninterrupted sleep during the night. Therefore, fatigue cannot be eradicated but must instead be effectively managed (ICAO, 2016:1/1). The comparison and validation of Fatigue Risk Management Systems (FRMS) in operational environments constitutes one of the priority research areas within the aviation industry (Weiland vd. 2013). In all circumstances, the goal of achieving “zero fatigue” is unrealistic; the primary objective is to minimize fatigue-related risks to an acceptable level (Hobbs et al., 2011:1). According to ICAO, fatigue may reduce the attention level of crew members and adversely affect their ability to operate an aircraft safely or to perform safety-related duties effectively (ICAO, 2022:1).

Fatigue is generally defined as a condition that causes a decline in cognitive and physical performance and reduces an individual’s capacity to work (Dawson & McCulloch, 2005). Although there are different types of fatigue (such as muscular fatigue, mental fatigue, psychomotor fatigue, and chronic fatigue), the concept of fatigue discussed within the context of fatigue risk management refers to “sleepiness arising from neurobiological processes regulating sleep and circadian rhythms,” or more simply, “the desire to sleep” (Dawson et al., 2011:550-551).

In the aviation and logistics industries, fatigue constitutes a serious risk factor for both occupational safety and operational efficiency. Research indicates that fatigue increases error rates in decision-making processes, prolongs reaction times, and leads to loss of attention (Caldwell, 2012; Van Dongen et al., 2003). This situation is of critical importance for maintaining flight safety and ensuring the uninterrupted execution of logistics operations (FAA, 2011.a).

The dynamic and demanding working conditions of these industries demonstrate that the effects of fatigue are not limited to individual health and performance but also have a direct impact on organizational safety culture and overall efficiency (Rogers et al., 2004). Therefore, managing fatigue risk requires a multidimensional and systematic approach. Within the framework of fatigue management, various strategies have been developed-such as optimizing rest periods for employees, improving shift scheduling, and implementing training and awareness programs (Dorrian et al., 2011).

However, the complex interactions among factors that cause fatigue create challenges in evaluating and prioritizing the effectiveness of these strategies (Gander et al., 2013). In this context, multi-criteria decision-making (MCDM) methods provide significant advantages in identifying cause-and-effect relationships among complex problems and supporting decision-making processes (Saaty, 2008). In particular, the DEMATEL (Decision Making Trial and Evaluation Laboratory) method analyzes both the direct and indirect relationships among factors, revealing the structural characteristics of the system and enabling the identification of critical determinants (Gabus & Fontela, 1972).

This study aims to identify the fundamental criteria influencing the level of fatigue among personnel working in the logistics and aviation sectors and to analyze the interactions among these criteria through a holistic approach. Within this scope, based on a comprehensive literature review and expert evaluations, eight criteria-workload intensity, shift schedule and working hours, sleep duration and quality, task continuity, psychological stress level, physiological conditions, training and awareness level, and institutional support mechanisms-were structurally modeled using the DEMATEL method and subsequently weighted through the BWM (Best-Worst Method).

This study stands out by providing a robust, dual-stage scientific foundation that deciphers the structural complexity of fatigue risk through an integrated MCDM framework. Unlike previous research that often treats fatigue factors in isolation, this study's originality lies in its holistic modeling of the intertwined causal relationships between logistics and aviation-two sectors that, despite their operational differences, share critical systemic fatigue triggers. By identifying not only the weights of individual criteria but also the underlying 'cause-and-effect' dynamics, the findings offer a strategic roadmap for fatigue mitigation. The importance of this work is manifested in its practical utility: it provides policymakers with a prioritized intervention list, moving beyond theoretical descriptions to actionable data. Ultimately, this research contributes to the enhancement of operational safety and the institutionalization of a resilient safety culture, bridging a significant gap in cross-sectoral fatigue risk management literature.

2. Literature Review

At present, the concept of FRMS is applied only within a limited scope, encompassing airlines and flight crews. Although the Turkish General Directorate of State Airports Authority (DHMİ) actively utilizes its Quality Management System (QMS) and Safety Management System (SMS), no specific studies have been conducted on excessive fatigue. The working and resting conditions of air traffic controllers (ATCs) are reviewed through annual internal audits; however, health and psychological assessments are limited to the biennial license renewal examinations. It has been identified that there is currently no specific system in Turkey for reporting excessive fatigue in air traffic control operations (Özden, 2019, pp.154–155). A study conducted in India examined the relationship between shift patterns, experience, sleep quality, and fatigue among ground handling staff aged 20–40, concluding that fatigue is a major cause of sleep loss and has a serious impact on flight safety (Kaur & Varma, 2024, p.94). In a study conducted in Portugal with ramp workers, it was found that even though there was no limit on duty hours, the 24-hour operational workload disrupted biological rhythms and caused fatigue. Therefore, it was emphasized that the development of FRMS for ramp personnel is important for both health and operational efficiency (Morais et al., 2023).

When examining national studies, one research study on aircraft maintenance technicians evaluated the effects of physical workload factors (representing only one aspect of fatigue) on employees using the DEMATEL method (Öztürk, 2021). A study focusing on ground handling services reported negative employee perceptions regarding shift work; however, no findings specifically related to fatigue were identified (Değirmencioğlu, 2019).

In a comparative study between pilots and physicians, the effects of fatigue on attention and the legal implications of errors caused by fatigue were discussed. The study concluded that FRMS are absent among physicians and insufficient among pilots (Mega & Yenerer Çakmut, 2021). Another academic study evaluated pilot crew assignment processes within the scope of fatigue risk management and emphasized that assignments should be conducted based on fatigue-related criteria (Şahinkaya, 2020).

A study examining the split work model revealed that irregular shift practices, indefinite overtime, and unfair workload distribution among passenger services and ramp personnel led to stress, insomnia, and fatigue (Koç, 2018). In a study on occupational health and safety in ground handling services, it was recommended that, to reduce the fatigue and accident risks associated with long working hours, the daily working hours for heavy and highly hazardous jobs should be limited to 6–7 hours, and annual overtime should not exceed 270 hours (Barut & Erdoğan, 2024, p.95). Furthermore, a study conducted with ground handling employees found that shift work and excessive overtime increased workload, leading to insufficient rest and work–family conflicts (Yılmaz et al., 2024, p.57).

MCDM methods enable the consideration of multiple factors in complex decision processes. In addition to methods such as the Analytic Hierarchy Process (AHP) developed by Saaty (2008), the DEMATEL method is particularly preferred for revealing cause–and–effect relationships within a system. Developed by Gabus and Fontela (1972), DEMATEL allows for the weighting of both direct and indirect effects, thereby clarifying complex problem structures.

Wang et al. (2014) applied the DEMATEL method in supply chain risk management to identify and prioritize critical risk factors. This approach can also be applied to fatigue risk management, as analyzing interactions among factors is crucial for identifying effective intervention points.

In recent years, the use of MCDM methods in the evaluation of fatigue-related factors has increased. In particular, the DEMATEL and BWM approaches provide suitable tools for identifying relationships and weighing among criteria in complex systems (Rezaei, 2015; Mi et al., 2019). Kumar and Yadav (2020) used the DEMATEL method to analyze human factors in the aviation sector and revealed the interrelationships among critical elements such as fatigue, lack of communication, and insufficient training. Similarly, Li et al. (2019) analyzed occupational safety risk factors in the construction industry using DEMATEL and identified priority areas for intervention. In the logistics sector, DEMATEL has also been effectively used to manage supply chain risks (Wang et al., 2014).

The application of the DEMATEL method to fatigue risk management in the present study offers an innovative contribution to the literature by demonstrating how this method can be operationalized in risk assessment processes based on human factors.

The reviewed literature indicates that most studies addressing fatigue risk factors have adopted individual or isolated approaches. Nevertheless, systematic models that consider the interrelationships among these factors are relatively limited. Moreover, comprehensive studies that simultaneously evaluate fatigue risk in both the logistics and aviation sectors using multi-criteria analytical methods remain few. This study aims to address this gap by:

• Examining eight fatigue risk factors holistically,
• Revealing the causal relationships among these factors using the DEMATEL method, and

• Determining the relative importance levels of the criteria through the BWM.

In this regard, the study provides decision-makers with a practical, prioritization-based framework for managing fatigue risk.

2.1. Conceptual Definition and Significance of Fatigue

Fatigue is defined as a complex state that leads to a decline in an individual's cognitive, emotional, and physical capacities (Dawson & McCulloch, 2005). Impairments in attention, concentration, and decision-making processes increase the significance of fatigue in terms of occupational safety and performance (Caldwell, 2012). In aviation, pilot fatigue is recognized as a critical factor that threatens flight safety. Van Dongen et al. (2003), through controlled experiments, demonstrated that chronic sleep deprivation can cause up to a 20% slowdown in pilots' reaction times. Such findings highlight the necessity of implementing systematic measures to combat fatigue. Additional factors that exacerbate fatigue in the aviation sector include intercontinental flights with time zone differences, consecutive night operations, and the nature of specific operational types (Wingelaar-Jagt et al., 2021). The identification, monitoring, and analysis of factors influencing fatigue, referred to as "Fatigue Factors" (Basaria, 2023) will enable the proactive management of fatigue-related risks.

2.2. Operational Impacts of Fatigue Risk Factors

A wide range of factors contributing to fatigue in the aviation and logistics sectors has been examined in the literature. Among these, shift schedules, workload intensity, sleep quality, psychological stress, task continuity, and physiological conditions stand out as major determinants (Lee et al., 2019; Rogers et al., 2004). For instance, Lee et al. (2019) investigated the impact of shift systems and extended working hours on fatigue levels among airport ground personnel and reported that irregular shift patterns adversely affect sleep quality, thereby reducing job performance.

Fatigue risk management strategies are addressed not only at the individual level but also at the institutional and organizational level. Gander et al. (2013) emphasized the impact of organizational factors on fatigue and stated that effective training programs, work planning, and employee support mechanisms are critical in fatigue management. In this context, a multidisciplinary approach should be adopted for fatigue management.

Around the world, fatigue risk management systems are used in various sectors such as air transportation, railway transportation, nuclear energy, mining, emergency services, and logistics (Özden, 2019: 29). In the aviation sector, ten items have been identified to measure the effectiveness of fatigue risk management: operational data analysis, scientific and biometric measurements, crew planning and rest periods, employee feedback, health and safety metrics, training effectiveness, fatigue prediction modeling, cost-benefit analysis, longitudinal studies, and regulatory compliance (Shaik, 2024). However, due to the cost and complexity of implementing a fatigue risk management system, the International Civil Aviation Organization (ICAO) has explicitly stated that such systems may not be suitable for all airlines (Miller, 2024).

The relationship between fatigue and safety has a complex dynamic, particularly in ultra-safe systems such as commercial aviation, because defense layers such as automation, teamwork, and standard procedures reduce the likelihood that the errors of fatigued individuals will lead to accidents (Gander et al., 2017, p.705). In aviation, fatigue increases the likelihood of errors among pilots and ground personnel, thereby endangering flight safety. According to the Federal Aviation Administration (FAA, 2011.b) report, fatigue-related accidents account for approximately 20% of all aviation accidents. Similarly, in the logistics sector, fatigue leads to operational problems such as delivery delays, mishandling of goods, and workplace accidents (Smith, 2018).

Rogers et al. (2004), in a study on nurses, revealed that long working hours pose risks to patient safety, a situation that parallels occupational safety issues in the logistics industry. In a study examining aircraft maintenance technicians, “Judgment Interference” (JI) was identified as one of the main factors causing these technicians (AMTs) to make erroneous decisions. Fatigue is the most significant component of JI, leading to memory lapses and intuitive processing errors (Eisenbeil, 2015).

As a result of rapid technological and scientific advancements, new approaches have emerged to complement existing fatigue risk management practices (Rangan et al., 2020). Chronobiologists and sleep scientists have demonstrated the impact of the biological clock and sleep–wake cycles on fatigue, explaining their contributions through biomathematical models (BMMs). Studies in the literature indicate that the biomathematical fatigue models used can accurately predict fatigue and attention performance, showing that the model’s predictions are consistent with both subjective fatigue assessments and cognitive performance data related to accident risk, thereby supporting the model’s validity (Morris et al., 2018). It has been suggested that, for more effective fatigue management, bureaucratic burden should be reduced, safety culture should be strengthened, and new sociotechnical and technological solutions should be explored (Bourgeois-Bougrine, 2020).

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3. Methodology

In this study, the key factors contributing to fatigue risk in the logistics and aviation sectors were identified, and the relationships and relative importance levels among these factors were analyzed. A two-stage MCDM approach was adopted: in the first stage, the DEMATEL method was employed to reveal the causal relationships among the criteria; in the second stage, the BWM was used to calculate the relative importance of the criteria.

The implementation process of the research consists of the following four main steps:

- **i.** Identification of eight key fatigue risk criteria through literature review and expert consultation,
- **ii.** Evaluation of interrelationships among the criteria using the DEMATEL method,
- **iii.** Weighting of the criteria using the BWM method,
- **iv.** Holistic interpretation of the findings and development of recommendations.

The identified criteria were analyzed using the DEMATEL method, one of the MCDM approaches, to reveal the causal relationships among them. Subsequently, the BWM was applied to determine the relative importance levels of these criteria. Through this process, the study scientifically identified which criteria should be considered as priority intervention areas in sectoral fatigue management. The developed model is expected to serve as a decision-support framework, guiding policymakers and organizational leaders in formulating effective strategies and policies for managing fatigue within the logistics and aviation industries.

The analysis conducted using the DEMATEL method reveals the interactions among these criteria and identifies the priority areas for intervention. The combined use of the DEMATEL and BWM enables the examination of complex interrelationships and provides decision makers with evidence-based policy recommendations. This integrated approach contributes to the establishment of a sustainable safety culture in both the logistics and aviation sectors.

In the analysis, data were collected from 20 experts working in the aviation and logistics sectors, including pilots, fleet managers, occupational safety specialists, and academics. The experts each had a minimum of eight years of sectoral experience and were employed in roles related to fatigue risk management.

Eight primary criteria were identified through an extensive literature review and consultations with industry professionals experienced in fatigue-related risk management. These criteria are presented in Table 1. The evaluation of these criteria was carried out through a two-stage method:

Table 1. Eight Key Criteria Related to Fatigue Risk

Code	Criterion
C1	Workload Intensity
C2	Shift Schedule and Working Hours
C3	Sleep Duration and Quality
C4	Task Continuity
C5	Psychological Stress Level
C6	Physiological Conditions
C7	Training and Awareness Level
C8	Organizational Support Mechanisms

3.1. The DEMATEL Method

The DEMATEL method is a multi-criteria decision-making technique developed to identify the mutual cause-and-effect relationships among criteria in complex systems (Gabus & Fontela, 1972). By considering both direct and indirect effects, this method enables the determination of the most influential and the most affected criteria within a system. In this way, decision-makers can visually and quantitatively understand which criteria should be prioritized (Saaty, 2008).

In this study, 20 expert participants were asked to rate the direct influence levels among the criteria on a scale from 0 (no influence) to 4 (very strong influence). The arithmetic means of the expert evaluations was then used to construct the direct-relation matrix, which was subsequently normalized and transformed into the total-relation matrix.

The classical DEMATEL procedure can be summarized as follows (Tzeng et al., 2007; Wu, 2008; Uygun et al., 2015):

1) Establishing the Direct-Relation Matrix: To obtain the Direct-Relation Matrix (M), experts or decision-makers evaluate the relationships among the criteria based on pairwise comparisons. In this study, the comparison scale proposed by Dey et al. (2012), which is widely used in the literature, was adopted.

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Table 2. Comparison Scale

Numerical Value	**Definition**
0	No influence
1	Low influence
2	Moderate influence
3	High influence
4	Very high influence

Since a criterion does not influence itself, all main diagonal elements in the matrix are equal to zero. If there is more than one expert, the arithmetic mean of the expert opinions is used. In a decision problem involving nnn criteria, *mij* represents the degree to which criterion *i* influences criterion *j* (Equation 1).

$$M = \begin{bmatrix} m_{11} & \cdots & m_{1j} & \cdots & m_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ m_{i1} & \cdots & m_{ij} & \cdots & m_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ m_{n1} & \cdots & m_{nj} & \cdots & m_{nn} \end{bmatrix}_{nxn} \quad ; i,j \in \{1,\dots,n\} \qquad \textbf{(1)}$$

2) Formation of the Normalized Direct-Relation Matrix: The Direct-Relation Matrix (M) is used to construct the normalized direct-relation matrix (D) by applying the equations presented below, as shown in Equation (2).

$$D = \frac{M}{k} \qquad \textbf{(2)}$$

$$k = max\left(\max_{1\leq i\leq n} \sum_{j=1}^{n} z_{ij}\, , max \sum_{i=1}^{n} z_{ij}\right) \qquad \textbf{(3)}$$

3) Formation of the Total Relation Matrix: The Total Relation Matrix (T) is used to represent the overall influence of the criteria. The indirect effects among the criteria are evaluated by utilizing the powers of the D matrix. This matrix illustrates the gradual decrease of indirect effects and ensures convergent inverse matrix solutions similar to those of an absorbing Markov chain (Hsu et al., 2013).

$$\begin{aligned} T &= D^1 + D^2 + D^3 + \cdots + D^h \\ &= D(I + D + D^2 + D^3 + \cdots + D^{h-1})(I - D)(I - D^{-1}) \qquad \textbf{(4)} \\ &= D(I - D^h)(I - D)^{-1} \end{aligned}$$

In Equation (4), I denotes the identity matrix. When lim Dh= $[0]n\times n$ and $h\rightarrow\infty$, the Total Relation Matrix is derived as follows:

$$T = \lim_{h=\infty} (D + D^2 + \cdots + D^h = \sum_{h=1}^{\infty} D^h = D(I - D)^{-1} \quad \textbf{(5)}$$

4) Identification of Influencing and Influenced Criterion Groups: The cause-and-effect values are determined by the sums of the rows and columns of the T matrix, represented by R and C, respectively. The formulations for these values are given in Equations (6) and (7). ri is the sum of the *i*th row and represents the *cause* value of criterion i. It indicates the total of direct and indirect effects transmitted from criterion *i* to other factors.

$$= \left[\sum_{j=1}^{n} t_{ij}\right]_{nx1}; \; i = 1, \ldots, n \quad \textbf{(6)}$$

Similarly, *cj* is the sum of the *j*th column and represents the effect value of criterion *j*. It indicates the total of direct and indirect effects received by criterion *i* from other criteria. In Equation (7), *T* denotes the transpose of the matrix *T*.

$$C = [c_j]_{1xn} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1xn}^{T}; \; j = 1, \ldots, n \quad \textbf{(7)}$$

For $i = j$ and i,j∈{1,2,…,n}, *ri+cj* represents the prominence of criterion *i,* that is, how important it is to others. A higher value of *ri+cj* indicates that the criterion has stronger interactions with other criteria, whereas a lower value suggests weaker interactions.

In addition, *ri+cj* values are used to classify the criteria into cause and effect groups. If *ri+cj* is positive for a criterion, it is identified as a **causal** criterion. Conversely, if *ri+cj* is negative, it is classified as an **effect** criterion.

5) Calculation of the Threshold Value and Construction of the Impact Diagram:

To facilitate the interpretation of the findings and to control the complexity of the system, a threshold value is used. Typically, the threshold value θ is calculated as the average of the elements in the Total Relation Matrix, as shown in Equation (8). Here, N=n×n represents the total number of elements in the matrix. In some cases, the threshold value can also be determined through brainstorming among decision-makers or experts.

$$\theta = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}}{N}, \quad i, j \in \{1, 2, \ldots, n\} \quad \textbf{(8)}$$

The threshold value is used when constructing the relation map. Only the relationships in the total direct-relation matrix that have values greater than the threshold are considered as mutual dependencies between the criteria. This approach aims to eliminate and filter out the criteria that have minimal influence on others.

The relationships exceeding the threshold value are plotted on the relation map, with R+C values represented on the horizontal axis and R−C values on the vertical axis. The R+C value, referred to as **"Prominence,"** indicates the overall strength of the effects given and received by a criterion. In summary, **Prominence** reflects the degree to which a criterion occupies a central role in the system. The R−C value, referred to as **"Relation,"** represents the net effect contributed by a criterion.

By examining the relation map, decision-makers can visually explore the complex causal relationships among the criteria and gain valuable insights to support the decision-making process.

6) Calculation of Criterion Weights:

Typically, a normalization process is applied to determine the importance weights of the criteria based on the Prominence (R+C) values, as shown in Equation (9) (Si et al., 2018).

$$\omega_i = \frac{r_i + c_i}{\sum_{i=1}^{n} r_i + c_i}, \quad i = 1,2,\dots,n \qquad \textbf{(9)}$$

(Dalalah et al., 2011) proposed an alternative formula (Equation 20–11) to measure the importance of the criteria. Here, ωi represents the vector length of each criterion on the Relation Map, measured from the origin point.

$$s_i = \sqrt{(r_i + c_i)^2 + (r_i - c_i)^2, i = 1,2,\dots,n} \qquad \textbf{(10)}$$

A normalization step is applied to obtain the final weights of the criteria to be used in the analysis.

$$\omega_i = \frac{s_i}{\sum_{i=1}^{n}(s_i)}, \quad \forall_i = 1,2,\dots,n \qquad \textbf{(11)}$$

3.2. Best–Worst Method (BWM)

The Best–Worst Method (BWM) (Rezaei, 2015) is an MCDM technique that uses pairwise comparisons. Its use has increased in recent years because, for computing criterion weights via pairwise comparisons, BWM offers several advantages over the widely used AHP. The formulation of BWM is straightforward to understand and implement. The core idea of the technique is that, when comparing two items in daily life, we implicitly rely on a reference point. Accordingly, BWM identifies the **best** and the **worst** criteria in a decision problem and compares them with the other criteria (reference comparisons) (Rezaei, 2015). Apart from these reference comparisons, no additional pairwise comparisons are made. Unlike AHP, which uses comparison **matrices**, BWM uses comparison **vectors**. Consequently, with nnn criteria, BWM requires *2n−3* comparisons, whereas AHP requires *n(n−1)/2* comparisons. Fewer comparisons reduce the potential for inconsistency; moreover, unlike DEMATEL, BWM yields a **consistency ratio** that indicates the reliability of the comparisons.

BWM can be used on its own to weight criteria and rank alternatives. It can also be employed in a hybrid fashion-performing only the weighting step while other techniques rank the alternatives-or, as in the present study, it can be used solely for **criterion weighting**.

A comprehensive review of BWM applications is provided by Mi et al. (2019), including a bibliometric analysis, the method's advantages and formulation, its integration with other MCDM approaches, existing challenges, and directions for future research.

The mathematical steps of the approach are detailed below (Rezaei, 2015; Beemsterboer et al., 2018).

1) Determination of the Decision Criteria (C): The set of criteria is essential for selecting the best alternative or ranking the available options. In the initial stage, a set of criteria *c1,c2,…,cn* consisting of nnn elements, is determined. To achieve this, a literature review may be conducted, brainstorming sessions may be organized, or expert opinions may be consulted. Since different groups of experts may have varying perspectives, it is possible to obtain different sets of criteria for the same subject matter.

2) Identification of the Best (B) and the Worst (W) Criteria: At this stage, experts are asked to identify the most important (best) and the least important (worst) criteria among the set. No pairwise comparisons are made in this phase; only the best and worst criteria are selected. If an expert identifies more than one criterion as the best or worst, they may arbitrarily choose one to represent the best or worst criterion.

3) Comparison of the Best Criterion with Other Criteria: The value *aij* represents the degree to which an expert prefers criterion *i* over criterion *j*. Typically, a Likert scale is used, representing preferences ranging from 1:equal importance to 9: absolute preference. A vector representing the preference of the best criterion over all other criteria is constructed as shown in Equation 12. Here, *ABj* indicates the preference level of the best criterion *B* over criterion *j*.

$$\mathrm{A_B} = (\mathrm{a_{B1}}, \mathrm{a_{B2}}, \dots \dots ., . \mathrm{a_{Bn}}) \qquad \textbf{(12)}$$

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4) Comparison of the Worst Criterion with Other Criteria: A vector representing the preference of all criteria over the worst criterion (W) is constructed as shown in Equation 13. In this vector, AjW indicates the preference of criterion j in comparison to the worst criterion.

$$A_W = (a_{1W}, a_{2W}, \dots \dots \dots, a_{nW})^T \quad \textbf{(13)}$$

5) Calculation of the Weights: The optimal weights *(w1∗,w2∗,...,wn∗)* are calculated by following the steps outlined below.

$$|w_B - a_{Bj} w_j| \leq \xi^L, \forall j \quad \textbf{(14)}$$

$$|w_j - a_{jw} w_w| \leq \xi^L, \forall j$$

$$\sum_j w_j = 1$$

$$w_j \geq 0, \forall j$$

6) Decision Matrix and Consistency: This step is performed to check the consistency of the comparisons and to assess the reliability of the results. The smaller the consistency ratio, the more consistent the comparisons are. The Consistency Ratio (CR) in the Best-Worst Method (BWM) can be calculated by combining the obtained ξL value with the corresponding consistency index, as shown below.

$$\text{Consistency Ratio} = \frac{\xi_L}{Consistency\ Index} \quad \textbf{(15)}$$

The consistency index in the formula represents the maximum possible value of ξL. Here, the consistency ratio lies within the interval ∈[0,1]. The closer the consistency ratio is to zero, the more consistent the resulting weight vector is- and vice versa. In general, a Consistency Ratio ≤0.1\leq 0.1≤0.1 indicates that the derived weight vector is acceptable.

4. Findings

At this stage of the study, previous research in literature on the main criteria for evaluating fatigue risk management in logistics and aviation management was examined in detail. Based on both the literature review and expert opinions, these criteria were identified and assessed. The eight criteria determined were used in the application phase of the study as the basis for evaluating factors affecting fatigue risk management. Expert opinions from 20 professionals in the field were collected to evaluate these criteria using the DEMATEL and BWM methods.

For the DEMATEL method, experts were asked to assess the degree of influence of each criterion on the others using a scale ranging from 0 to 4 through a structured survey. The evaluations obtained from the survey were analyzed using the DEMATEL method, and the relative importance ranking of the criteria was determined.

As an alternative approach, in the second phase of the study, the weights of the criteria influencing fatigue risk management were calculated using BWM. Experts first identified the best and the worst criteria within the set and then conducted reference comparisons among the remaining criteria. Finally, the criteria were ranked according to their calculated weights, and the results obtained from the two methods were presented separately.

DEMATEL Results:

First, the analysis of the main set of criteria affecting fatigue risk management was conducted using the DEMATEL method. The set of criteria was presented to 20 experts in the fields of supply chain management and logistics for pairwise comparison. The experts rated the level of interaction between the criteria on a scale from 0 (no influence) to 4 (very strong influence).

Table 1 presents the **Direct Relation Matrix**, calculated by averaging the expert evaluations for each pair of criteria. Following the computational steps of the DEMATEL method, the **cause**-and-effect criteria were identified. Subsequently, the **weighted ranking of the criteria** was determined and presented.

Table 3. Decision Matrix of Fatigue Risk Management Criteria

C	C1	C2	C3	C4	C5	C6	C7	C8
C1	0.000	3.611	2.833	3.556	3.111	3.167	1.722	1.444
C2	3.833	0.000	2.833	3.611	2.944	3.111	1.500	1.111
C3	2.667	3.444	0.000	3.111	3.222	3.056	1.500	0.667
C4	3.278	3.444	2.444	0.000	2.778	2.444	1.667	1.500
C5	3.000	3.056	3.111	2.667	0.000	2.333	1.833	1.333
C6	3.222	2.778	2.333	2.889	2.611	0.000	1.222	0.889
C7	1.833	1.444	1.222	2.222	1.833	1.833	0.000	1.667
C8	2.000	2.222	0.667	1.944	2.056	1.333	1.611	0.000

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Table 4. Normalized Direct Relation Matrix

C	C1	C2	C3	C4	C5	C6	C7	C8
C1	0.0000	0.1857	0.1457	0.1829	0.1600	0.1629	0.0886	0.0743
C2	0.1971	0.0000	0.1457	0.1857	0.1514	0.1600	0.0771	0.0571
C3	0.1371	0.1771	0.0000	0.1600	0.1657	0.1571	0.0771	0.0343
C4	0.1686	0.1771	0.1257	0.0000	0.1429	0.1257	0.0857	0.0771
C5	0.1543	0.1571	0.1600	0.1371	0.0000	0.1200	0.0943	0.0686
C6	0.1657	0.1429	0.1200	0.1486	0.1343	0.0000	0.0629	0.0457
C7	0.0943	0.0743	0.0629	0.1143	0.1143	0.0943	0.0000	0.0857
C8	0.1029	0.1143	0.0343	0.1000	0.1057	0.0686	0.0829	0.0000

The normalized direct relation matrices (Table 4) were obtained by multiplying the direct relation matrix by the largest total value (k = 19.44).

The Total Relation Matrix (Table 5) was obtained by applying Equation (5).

Table 5. Total Relation Matrix

	C1	C2	C3	C4	C5	C6	C7
C1	1,0427	1,2058	0,9913	1,1976	1,1205	1,0659	0,6696
C2	1,1934	1,0351	0,9802	1,1856	1,1005	1,0515	0,6520
C3	1,0906	1,1260	0,8057	1,1075	1,0561	0,9976	0,6184
C4	1,0976	1,1098	0,9019	0,9539	1,0237	0,9586	0,6175
C5	1,0734	1,0822	0,9181	1,0618	0,8875	0,9434	0,6175
C6	1,0286	1,0172	0,8432	1,0160	0,9538	0,7877	0,5602
C7	0,7584	0,7465	0,6163	0,7743	0,7369	0,6820	0,3825
C8	0,7405	0,7522	0,5720	0,7381	0,7056	0,6387	0,4446

The Total Relation Matrix illustrates all direct and indirect relationships among the criteria. Since the criterion set includes eight criteria, there are 64 relationships in total, indicating a high degree of interconnection. However, some of these relationships are not significant. To identify the critical relationships and analyze them more effectively, the threshold value was computed as 0.8378 based on the average of the matrices. The mutual relationships exceeding this threshold are highlighted in gray in **Table 5**.

When examining the Total Relation Matrix, several patterns become evident. For instance, it is observed that **criteria C7 and C8** do not receive any significant influence from other criteria. Similarly, **criteria C1, C2, C4, and C6** do not exert a meaningful influence on other variables. In contrast, **criteria C3, C5, and C8** appear to have the highest number of influences exceeding the threshold value, indicating that they play a more dominant role within the system.

The Prominence and Relation values calculated from the data obtained in the Total Relation Matrix are presented in Table 6. Based on these values, the criteria were classified into Cause-and-Effect groups. In addition, the ranking of each criterion was determined. The criterion weights were computed using Equations (20)–(11).

Based on the analysis of the table, the cause group includes criteria C4, C6, and C7, while the remaining criteria belong to the effect group. According to the Prominence (R + C) values, the criteria with the highest interactions with others are C1, C2, C3, and C5, which also rank among the top three in the importance order. Within the cause group, C4 is identified as the most critical criterion, whereas C1 and C2 are the most prominent in the effect group.

Table 6. Criteria in Cause–Effect Groups

Criterion	R	C	R + C	R - C	Definition
C1	6.3409	6.3709	12.7118	-0.0301	Effect/ Result
C2	6.1079	6.3533	12.4612	-0.2455	Effect/ Result
C3	5.5378	5.5850	11.1228	-0.0472	Effect/ Result
C4	6.4515	6.3973	12.8488	0.0542	Cause/ Driver
C5	5.4668	5.5366	11.0034	-0.0698	Effect/ Result
C6	6.7144	6.4269	13.1413	0.2875	Cause/ Driver
C7	4.1895	4.0476	8.2371	0.1419	Cause/ Driver
C8	5.5275	5.6187	11.1463	-0.0912	Effect/ Result

Table 7 presents the ranking of importance for fatigue risk management criteria as calculated by the DEMATEL method.

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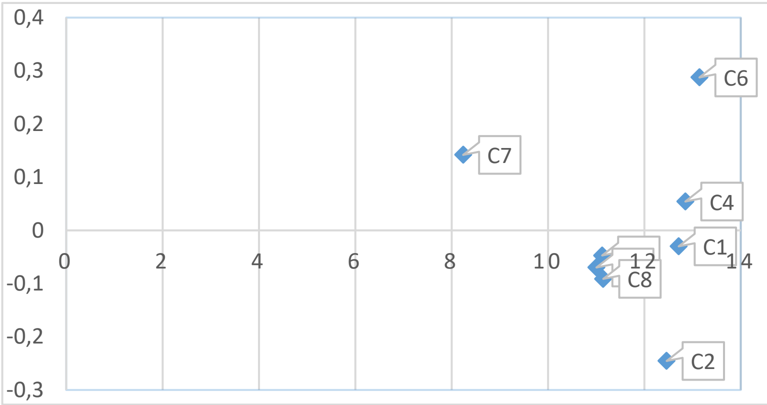
Table 7. Ranking of Fatigue Risk Management Criteria Weights According to the DEMATEL Method

Criteria	Weight	Rank
C1	12.71186958	3
C2	12.46363683	4
C3	11.12288338	6
C4	12.84889669	2
C5	11.00366036	7
C6	13.14442339	1
C7	8.238328529	8
C8	11.14662455	5

In Figure 1, the cause–and–effect diagram illustrating the relationships among fatigue risk management criteria is presented.

Figure 1. Cause–Effect Diagram of Fatigue Risk Management Criteria



BWM Analysis Results

In this study, within the analysis conducted using the BWM, 10 experts selected one of the eight criteria as the **"best"** (most important) and another as the **"worst"** (least important) criterion. Subsequently, pairwise comparisons were carried out based on these selections.

Following the identification of the best and worst criteria, two evaluation matrices were developed:

- A **Best-to-Others (BO)** matrix, where the importance of the best criterion relative to the others was rated on a scale from **1 to 9**, and

- An **Others-to-Worst (OW)** matrix, where the importance of the other criteria relative to the worst criterion was similarly rated from **1 to 9**.

Table 8 presents the main criterion evaluations provided by Decision Maker 1.

Table 8. Main Criterion Evaluations of Decision Maker 1 (DM1)

Step 1	**Identification of the Best and the Worst Criteria**							
	The Best Criterion			C3	**The Worst Criterion**			C8
Step 2	**Best-to-Others Evaluation (A_B)**							
	C1	C2	C3	C4	C5	C6	C7	C8
	5	6	1	4	7	6	3	9
Step 3	**Others-to-Worst Evaluation (A_W)**							
	C1	C2	C3	C4	C5	C6	C7	C8
	3	4	5	4	6	5	3	1

According to **Table 8**, the “best” (most important) and “worst” (least important) evaluation vectors were determined as follows:

A_B = **{5, 6, 1, 4, 7, 6, 3, 9}** and A_W = **{3, 4, 5, 4, 6, 5, 3, 1}.**

Starting from **Equation (3)** up to **Equation (10)**, a **linear programming model** was constructed and analyzed. Based on this analysis, the **main criterion weights** for **Decision Maker 1 (DM1)** were calculated as follows:

C1 = 0.12, C2 = 0.14, C3 = 0.18, C4 = 0.10, C5 = 0.16, C6 = 0.12, C7 = 0.08, C8 = 0.10

The **consistency ratio** was computed as **ξ = 0.125**.

By applying all the steps of the BWM and using the pairwise comparisons obtained from each decision maker through the surveys, a linear programming model analysis was conducted, and the weights of the main criteria were obtained as shown in Table 9.

During the evaluation of the criteria, each expert’s assessments were first analyzed individually. Then, the average of the results from ten experts was calculated to obtain the final criterion weights. In this study, the geometric mean was preferred over the arithmetic mean to eliminate the potential distortion caused by extreme values in the data.

After calculating the geometric means, a normalization process was performed again, since the sum of geometric means does not necessarily equal 1,

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unlike arithmetic means. The average consistency ratio (ξ) for all experts was calculated as ξ = 0.125, which is well below the BWM threshold of 0.25. This indicates that the experts' comparisons were highly consistent.

The individual criterion weights of each expert, as well as the average criterion weights, are presented in Table 9.

Table 9. Consistency Ratios and Average Weights for Each Decision Maker

Criterion	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	DM9	DM10	Weights ω
C1	0,12	0,14	0,15	0,13	0,1	0,11	0,12	0,13	0,14	0,13	0,127
C2	0,14	0,13	0,14	0,1	0,12	0,13	0,11	0,12	0,15	0,14	0,128
C3	0,18	0,12	0,11	0,09	0,14	0,12	0,13	0,1	0,13	0,12	0,124
C4	0,1	0,11	0,13	0,12	0,13	0,14	0,1	0,12	0,12	0,11	0,118
C5	0,16	0,15	0,14	0,18	0,11	0,13	0,14	0,13	0,11	0,13	0,138
C6	0,12	0,13	0,11	0,14	0,12	0,12	0,15	0,14	0,11	0,13	0,127
C7	0,08	0,12	0,11	0,12	0,14	0,13	0,13	0,14	0,12	0,12	0,121
C8	0,1	0,1	0,11	0,12	0,14	0,12	0,12	0,12	0,12	0,12	0,117
ξ	0,1212	0,1241	0,1240	0,1226	0,1242	0,1247	0,1241	0,1244	0,1243	0,1247	0,125

The ranking of the criteria by their weights is as follows:

Table 10. Ranking of Criteria Weights

Criterion	Weight (ω)
C1 – Workload Intensity	0.127
C2 – Shift Schedule and Working Hours	0.128
C3 – Sleep Duration and Quality	0.124
C4 – Task Continuity	0.118
C5 – Psychological Stress Level	0.138
C6 – Physiological Conditions	0.127
C7 – Training and Awareness Level	0.121
C8 – Organizational Support Mechanisms	0.117

In the weighting analysis conducted using the BWM, criterion **C5** emerged as the most significant individual factor influencing employee fatigue. Criterion **C8**, on the other hand, was evaluated with a lower weight, reflecting its more indirect and external effects on the system.

Comparative Evaluation of DEMATEL and BWM Results

When the DEMATEL and BWM analyses are evaluated together, a meaningful consistency is observed between the systemic influence of the criteria and their individual importance levels. For example, **C1 – Workload Intensity** and **C2 – Shift Schedule and Working Hours** emerged as the most affected criteria in the DEMATEL analysis and were also ranked among the top three criteria with the highest weights in the BWM analysis.

This finding indicates that these criteria are components that not only have a direct impact on individual fatigue formation but also generate consequences at the systemic level. Similarly, **C5 – Psychological Stress Level**, although not central within the system, received the highest weight in the BWM results, highlighting its decisive influence on individual fatigue.

5. Conclusion

This study was conducted to systematically analyze the key determinants of fatigue risk experienced by personnel working in the logistics and aviation sectors. Based on literature and expert opinions, eight main criteria were identified and evaluated in terms of their interaction structure using the DEMATEL method; subsequently, their relative importance levels were calculated through the BWM method.

The findings reveal that fatigue is not solely an individual phenomenon but rather a multidimensional risk factor arising from the interaction of structural and organizational elements.

According to the DEMATEL analysis, the criteria "K4 – Task Continuity," "K6 – Physiological Conditions," and "K7 – Training and Awareness Level" were identified as causal (influential) factors within the system, while "K1 – Workload Intensity" and "K2 – Shift Schedule and Working Hours" emerged as the most affected (result) criteria. This finding indicates that task planning and physical/psychological readiness play a central role in the background of fatigue development.

In the BWM analysis, based on expert evaluations, the criterion with the highest importance was determined to be "K5 – Psychological Stress Level." It was followed by criteria such as "K2 – Shift Schedule and Working Hours," "K1 – Workload Intensity," and "K6 – Physiological Conditions," which are directly related to the operational environment. This supports the notion that external conditions challenging employees' mental and physical capacities are key

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determinants of fatigue. Conversely, "K8 – Organizational Support Mechanisms" had the lowest weight in the analysis and appeared to have a more indirect sphere of influence. Although institutional support and training may seem less urgent in the short term, they hold critical potential for long-term risk mitigation.

Considering these findings, it is evident that fatigue risk management requires integrated strategies at both individual and organizational levels. Below are several recommendations for sectoral implementation:

1. **Improvement of Shift Scheduling:** Shift cycles should be redesigned to support employees' biological rhythms, and flexible scheduling should be implemented to allow sufficient rest and sleep periods.

2. **Enhancement of Physiological Conditions:** Workplaces should undergo ergonomic improvements, rest areas should be upgraded, and employees' physiological conditions should be monitored through regular health screenings. In addition, technological systems capable of objectively tracking fatigue levels should be established.

3. **Training and Awareness Programs:** Regular awareness training sessions should be organized for all employees regarding the symptoms, causes, and consequences of fatigue. These programs should aim not only to transfer knowledge but also to promote behavioral change.

4. **Strengthening Organizational Support Mechanisms:** Psychosocial support systems (such as psychological counseling and stress management workshops) should be expanded institutionally, and open communication channels should be established between managers and employees.

The findings of this study demonstrate that fatigue risk management can be effectively analyzed through multi-criteria decision-making (MCDM) methods. However, to generalize these results to a broader context, it is necessary to apply DEMATEL and BWM analyses in different sectors and sub-professional groups, incorporate objective measurements of fatigue risk (e.g., biometric data, performance scores), and compare them with the current analytical outcomes. Moreover, the developed intervention strategies should be monitored and evaluated over the long term.

The main limitation of this study is that the analyses were conducted solely based on qualitative expert opinions. Future research should include objective data (such as biometric fatigue measurements) to enhance the accuracy of the model. Additionally, comparative analyses across different countries and occupational groups (e.g., flight crews, maintenance personnel, warehouse staff) would be valuable for testing the generalizability of the results. The DEMATEL and BWM methods can also be integrated with other MCDM techniques such as AHP, ANP, TOPSIS, or VIKOR to develop more comprehensive models.

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