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HAVAYOLU AKSAKLIK YÖNETİMİ KARARLARINI ETKİLEYEN FAKTÖRLERİN R-SWARA YÖNTEMİYLE DEĞERLENDİRİLMESİ

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ÖZ

Amaç: Bu çalışmanın amacı, havayolu operasyonlarında gerçekleşen aksaklıklara yönelik operasyonel kararları etkileyen temel kriterleri belirlemek ve bu kriterlerin önem ağırlıklarını analiz etmektir.
Yöntem: Bu bağlamda, aksaklık yönetimi kararlarını etkileyen potansiyel kriterler için bir literatür taraması yapılmış ve sonrasında nihai kriterleri belirlemek için havayollarının operasyon kontrol merkezlerinde görev yapan uzmanlarla yarı yapılandırılmış görüşmeler yapılmıştır. Ayrıca, bu faktörlerin göreceli önem ağırlıkları uzman görüşü udaklı R-SWARA kriter ağırlıklandırma yöntemiyle belirlenmiştir..
Sonuçlar: Bulgular uçuş emniyetinin havayollarının aksaklık yönetimi süreçlerinin karar alma sürecinde en önemli kriter olduğunu ortaya koymaktadır. Güvenlik de mevcut araştırmada ikinci en önemli kriter olarak sıralanmıştır. Diğer kriterlerin sıralamaları da incelenmesi gereken bilimsel çıktılar olarak önem arz etmektedir.
Özgün Değer: Havayolu aksaklık yönetimi üzerine yapılan araştırmalar, havayollarının operasyonel aksaklıklara verdikleri yanıtların optimize edilerek aksaklıkların hafifletilmesi ve yeni çözüm modellerinin geliştirilmesi üzerine odaklanmaktadır. İlgili çalışmalar, aksaklıkların olumsuz etkilerini en aza indirmek için yoğunlukla matematiksel optimizasyon modelleri kullanmıştır. Ancak bahsedilen aksaklıklara verilen cevaplarda hangi kriterlere öncelik tanınması gerektiğine yönelik karar verme yöntemlerini kullanan bir araştırmaya rastlanmamıştır. Bu çalışmada karar verme problemi olarak bu konunun ele alınması, aksaklık yönetim probleminin çözümünde etkili olan perspektiflere dair makro bir bakış açısı sağlayacaktır.

AN ASSESSMENT OF FACTORS INFLUENCING AIRLINE DISRUPTION MANAGEMENT DECISIONS THROUGH R-SWARA METHOD

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ABSTRACT

Objective: This study aims to identify the key criteria determining operational decisions to disruptions in airline operations and analyze the importance weights of these criteria.
Method: In this context, a literature review was conducted to identify potential criteria influencing disruption management decisions. Subsequently, semi-structured interviews were held with experts working in airline operations control centers to finalize the criteria. Additionally, the relative importance weights of these factors were determined using the expert-focused R-SWARA (Rough Step-wise Weight Assessment Ratio Analysis) method.
Results: The findings reveal that flight safety is the most significant criterion in the decision-making process of airlines' disruption management. Security ranked as the second most important criterion in the current study. The rankings of other criteria also provide valuable scientific insights for further examination.
Originality: Research on airline disruption management primarily focuses on optimizing responses to operational disruptions and developing new solution models. These studies have predominantly employed mathematical optimization models to minimize the adverse effects of disruptions. However, no research has been found that utilizes decision-making methods to prioritize the criteria influencing responses to such disruptions. Addressing this topic as a decision-making problem in this study provides a macro perspective on the perspectives influencing the resolution of disruption management challenges.

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1. Introduction

Air transport industry is among one of the most resilient industries with its ability to recover from crisis such as oil crisis, 2008 financial crisis and Covid-19 outbreak. However, the air service is not always seamless due to adverse weather conditions, technical malfunctions, negative seasonality effects, capacity constraints, planning errors and externalities etc. Accordingly, disruptions in the airline industry occur as a result of interruptions in flight schedules for various reasons, and these interruptions typically manifest as cancellations, delays, the holding, and diversions. Such disruptions lead to significant financial losses and diminish passenger satisfaction. According to Eurocontrol data, in 2023, nearly 30% of flights arrived more than 15 minutes late. This rate is higher than in 2022 and significantly worse than pre-pandemic levels in 2019 (EUROCONTROL, 2024). Factors such as adverse weather conditions, airport restrictions, limited number of ground handling staff, and turnout by air traffic controllers are cited as primary causes of these delays and cancellations (EUROCONTROL, 2023; Evler et al., 2022; Ogunsina et al., 2021). Managing these disruptions is not just essential, it's urgent, as they alter flight schedules and influence components related to ongoing and subsequent flights. In this context, it is important to develop solutions considering various elements such as flight network, passenger, crew, aircraft, airport, and ground handling services (Ogunsina et al., 2021). From the passenger's perspective, dissatisfaction resulting from the failure of their journey to proceed as planned, along with the cancellation of connecting flights and compensations for accommodation and meals, constitutes significant consequences of these disruptions (Barnhart et al., 2002; Bratu and Barnhart, 2005).

Additionally, issues concerning the crew arise, including the expiration of their duty hours, the necessity of overnight stays, and the potential for missing subsequent flights (Wen et al., 2021). In this context, multifaceted problems arise, such as reallocating aircraft based on their capacities or assigning different aircraft to the same flight (Lonzius & Lange, 2017). As air transport systems become increasingly congested, especially during peak travel times, airlines must implement effective strategies to manage these disruptions and minimize their impact. (Hassan et al., 2021; Wang & Zhao, 2020). In this regard, they resort to operational solutions such as task rescheduling, crew recovery, fleet recovery, alterations in cruise speed, gate reassignment, route changes, and additional passenger services. Effective disruption management enhances operational efficiency and strengthens customer loyalty and compliance with regulatory standards, which are crucial for sustaining competitive advantage.

Research on airline disruption management focuses on reviewing the responses of airlines to operational disruptions (Dudley and Clarke, 1998; Hassan et al., 2021), modeling the disruption problem for responses such as aircraft recovery, crew recovery, and passenger recovery with multiple variables and assumptions through exact optimization (Aktürk et al., 2014; Arıkan et al., 2017; Lee et al., 2020; Santos et al., 2017), metaheuristic methods (Liu et al., 2010; Vink et al., 2020), and hybrid heuristic methodologies (Mansi et al., 2012; Wu et al., 2017). Dudley and Clarke (1998) presents the first comprehensive review of practices within airline operations control centers for irregular operations. They propose a decision framework for reallocating aircraft to scheduled flights after disruptions. Another literature review conducted by Filar et al. (2001) finds that researchers in operational airline disruptions have employed various methods. The study reports on the success of linear programming, integer programming, dynamic programming, network optimization, queuing theory, flexible manufacturing systems, and simulation techniques within airline recovery literature. Clausen et al. (2010) similarly provide an overview of model formulations for aircraft and crew scheduling problems, highlighting similarities in solution approaches for planning and recovery problems. They note that proactive measures complement disruption management and briefly review research on schedule robustness in airline schedules.

In their review study, Hassan et al. (2021) note that recent studies have adopted integrated approaches to model crew, passenger, and aircraft recovery problems. Additionally, they emphasize the increasing number of functions employed in research to represent the operational context better. The growth in computational power has driven the development of models, facilitating the integration of detailed operational aspects, such as multi-aircraft assignment, travel plan reorganization, and cruise speed control, within the same model. Accordingly, various modelling approaches are vastly utilized in the airline disruption management literature.

Studies addressing operational disruptions often focus on assignment problems such as crew assignment, aircraft assignment, gate assignment, maintenance scheduling, and flight network reorganization, with objectives to maximize cost-efficiency, revenue, and passenger satisfaction, as well as to control cruise speed and reduce carbon emissions (Kohl et al., 2007). Yu et al. (2003) examine Continental Airlines' program for reducing crew-related disruptions, focusing on cost and revenue as primary criteria for resolving crew-related issues. Petersen et al. (2012) aim to provide a passenger-friendly solution by considering crew assignments, schedule changes, aircraft adjustments, and the cost of passenger dissatisfaction. The study finds that short-term crew assignments can prevent disruptions; however, extended scenarios require more substantial resources and higher costs. Chen and Chou (2017) optimize crew utilization during disruptions, referencing criteria such as crew availability and task count that vary with the length of disruptions. Their model simulates real-life operational disruptions and provides Pareto solutions, highlighting its effectiveness in producing multiple recovery plans for decision-makers. In terms of aircraft assignment, Wu et al. (2017) consider flight routes according to departure and arrival stations in their linear programming approach to solve airline disruption problems. The cost of delays and cancellations and the importance of subsequent flights from arrival stations serve as criteria in this approach. Vink et al. (2020) aim for a swift resolution using a heuristic method that iteratively solves the selection of airline fleets. The proposed approach applies to airlines with heterogeneous fleets and airlines serving both point-to-point and hub-and-spoke networks. Decision-making criteria include costs associated with delays and cancellations, route and maintenance schedule adjustments, and aircraft type for subsequent flights. Arıkan et al. (2017) develop a flight network-based approach to represent integrated airline recovery issues. This approach accounts for the flow of aircraft, crew members, and passengers across the airline's flight network. The network structure, flight duration, aircraft and crew compatibility, flight cancellations, aircraft speed adjustments, and passenger satisfaction costs are evaluated. The study suggests that aircraft speed decisions can be applied across the flight network.

In recent years, research has seen a rise in adopting a holistic approach considering multiple objectives. Mansi et al. (2012) consider cost minimization and potential passenger impact in the recovery process, aiming to resume normal operations as quickly as possible. Jozefowiez et al. (2013) optimize passenger reassignment and minimize airline costs within the limited flight schedule, testing the algorithm with real-world data and large-scale examples for computational efficiency. Bouarfa et al. (2016) focus on the airline operations control centre's issue of disruption management, examining multi-agent coordination models across four scenarios. They note that airline size, type of operations, base, and culture also impact disruption management. Santos et al. (2017) conduct a case study using linear programming and accurate operational data, noting that runway, taxiway, and airport factors affect disruption management. Miranda and Oliveira (2018) show that increased competition in intercity markets reduces flight delays and cancellations. They also emphasize the role of airport congestion and slot management in disruption management.

As can be seen from the rich literature, airline disruption management problem is multifaceted with scenario specific nature. Moreover, the relevant studies have been using mathematical optimization models to minimize the adverse effects of disruptions. However, to the best of our knowledge, there is no study dealing with the conditions that lead airlines to decide which response to apply against disruptions based on multi criteria decision making approach. The present study aims to address this gap by examining the primary factors/criteria determining airlines' strategies in disruption management, focusing on criteria such as safety, security, cost and customer satisfaction. Through expert interviews and criteria weighting methods, the study aims to answer the questions, "What are the factors determining airlines' responses to disruptions?" and "What are the importance levels of these criteria?" The findings of this study have the potential to significantly improve the industry's understanding of how airlines prioritize and implement effective response mechanisms, thereby supporting the development of resilient and adaptable operational practices. In this context, the second section of the study presents the methodology adopted, while the third section presents the findings. Finally, the fourth section outlines the discussion and conclusions while offering recommendations for future decision making research in the airline disruption management.

2. Methodology

The method of this study consists of two phases, namely constructing the criteria and weighting the criteria. To address the first research question, semi-structured interviews were conducted with three experts working as flight dispatchers or supervisors in the operations control centers of two different airlines in Türkiye. Semi-structured interviews are one of major qualitative data collection methods used in qualitative research methods and represent a hybrid approach between informal conversational interviews and formal structured interviews (Patton, 2015). Additionally, in semi-structured interviews, researchers can obtain in-depth information on the subject with probing questions in addition to the main questions asked. Probe questions allow the researcher to direct the participant and elaborate the answer received (Sandy & Dumay, 2011). The main question asked to participants is outlined below:

• What are the factors (criteria) that affect the operational decisions you take when responding to disruptions such as cancellations and delays?

Before the interviews, the potential criteria were extracted from the airline disruption management literature to be prepared for the interview process. Table 1 gives in-depth information regarding three interviews that were conducted in this study. The interviews were recorded and stored, the participants were also given voluntary participation form to fill up.

Table 1. Details of semi-structured interviews

Participants / Decision makers	*Position*	*Tenure*	*Date of interview*	*Duration*	*Interview method*
DM1	Flight dispatcher	20 years	25.09.2024	70 min	Video conference
DM2	Long haul flight dispatcher	25 years	25.09.2024	70 min	Video conference
DM3	Ground Operations Control Center Supervisor	6 years	08.10.2024	22 min	By phone

To answer the second research question, "What are the importance levels of these criteria?", a quantitative criterion weighting method, namely Rough SWARA (R-SWARA) was preferred. Developed by Zavadskas et al. (2018), R-SWARA is a version of classic SWARA (Keršuliene et al., 2010) that can be used in environments with uncertain and incomplete information. The method is fit for multi criteria decision making problems with qualitative criteria. As detailed by Pamučar et al. (2018), rough set theory makes it possible to analyze uncertain or incomplete data sets. In other words, R-SWARA is applied in situations where decision makers cannot clearly identify some information or where they are not completely sure. In our case, the criteria are potentially qualitative as the disruption cases dependent on specific cases which makes hard to collect quantitative values for each criterion. R-SWARA are executed with following steps (Zavadskas et al., 2018):

Step 1: Defining a set of criteria that participate in a decision-making process.

Step 2: Ranking of criteria based on their importance according to the experts (decision makers/DMs).

Step 3: Converting individual responses of DMs into a group rough matrix. Herein, lower approximation ($Aprlow(C_j)$), upper approximation ($Aprup(C_j)$), and boundary region ($Bnd(C_j)$) of each criterion is found. This is achieved by implementing following six equations.

$$Aprlow(C_j) = \{Y \epsilon U \mid R(Y) \leq C_j\} \quad (1)$$

$$Aprup(C_j) = \{Y \epsilon U \mid R(Y) \geq C_j\} \quad (2)$$

$$Bnd(C_j) = \{Y \epsilon U \mid R(Y) \neq C_j\} = \{Y \epsilon U \mid R(Y) > C_j\} \cup \{Y \epsilon U \mid R(Y) < C_j\} \quad (3)$$

Then C_j can be shown as a rough number located in an interval ($RN(C_j)$). It is determined by its related lower limit ($Limlow(C_j)$) and upper limit ($Limup(C_j)$) where:

$$Limlow(C_j) = \frac{1}{Mlow} \sum R(Y), Y \in Aprlow(C_j) \quad (4)$$

$$Limup(C_j) = \frac{1}{Mup} \sum R(Y), Y \in Aprup(C_j) \quad (5)$$

$$RN(C_j) = [Limlow(C_j), Limup(C_j)] \quad (6)$$

Step 4: Normalizing $RN(C_j)$ matrix to obtain $RN(S_j)$ matrix

$RN(S_j) = [s_j^L, s_j^U] = \frac{[c_j^L]}{\max[c_r^L]}; \frac{[c_j^U]}{\max[c_r^U]}$; first element of the matrix $RN(S_j)$=[1.00,1.00](7)

Step 5: Calculating $RN(K_j)$ matrix

$$RN(K_j) = [s_j^L + 1, s_j^U + 1], j = 2,3,\dots,m \quad (8)$$

Step 6: Determining the matrix of $RN(Q_j)$ for recalculated weights

$$RN(Q_j) = \left[q_j^L = \{\frac{q_{j-1}^L}{k_j^U}; j > 1, q_j^U = \{\frac{q_{j-1}^U}{k_j^L}; j > 1\right], RN(Q_j) = 1; j = 1 \quad (9)$$

Step 7: Calculating the matrix of relative weight values $RN(W_j)$

$$RN(W_j) = [w_j^L, w_j^U] = \frac{[q_j^L, q_j^U]}{\sum_{j=1}^{m}[q_j^L, q_j^U]} \quad (10)$$

3. Findings and analysis

The airline disruption management evaluation criteria, finalized through literature review and expert opinions, are presented in Table 2 with their descriptions. For the first research question, according to the data from expert opinions, we find seven criteria that are important in choosing the best possible response to disruption scenarios, namely environmental impact, punctuality/time, cost, compliance with the available schedule, flight safety, flight security, and passenger satisfaction.

Table 2. Airline disruption management evaluation criteria

Criteria code	Criteria descriptions
C1	**Environmental impact** – The criterion related to the environmental effects of the operational response to a disruption, including carbon emissions, energy and water usage, noise exposure, potential waste generation, etc.
C2	**Punctuality/time** – The criterion concerning how much delay an operational response may cause or how potential cancellations might affect passengers' total travel time.
C3	**Cost** – The criterion regarding the direct and indirect financial costs of the operational response.
C4	**Compliance with the available schedule** – The criterion regarding the compliance of the operational response with the company's other flight schedules, crew and equipment planning, etc.
C5	**Flight safety** – The criterion concerning how the operational decision might impact flight safety.
C6	**Flight security** – The criterion concerning how the operational response might affect flight security (e.g., unruly passenger behavior, proximity to no-fly zones, etc.).
C7	**Passenger satisfaction** – The criterion concerning the impact of the operational response on passenger satisfaction.

For the second research question, the criteria finalized as a result of expert interviews and literature review were weighted using the R-SWARA steps given in the previous section. In this context, tables related to the importance ranking of the criteria were initially created based on the responses provided by three expert decision-makers, whose details are also given in the methods section. Subsequently, the scores provided were entered into a table using Microsoft Excel, and the R-SWARA processing steps were applied to obtain the criteria weights.

The importance rankings given by the expert DMs for the criteria are shown in Table 3. According to the table, while flight safety (C5) is considered the the most important by two DMs, compliance with the available schedule (C4) is found to be the least important by two DMs.

Table 3. Decision makers' ranking of importance for the airline disruption management criteria

Criteria		Decision makers' ranking		
		DM1	**DM2**	**DM3**
C1	**Environmental impact**	5	5	7
C2	**Punctuality/time**	4	4	1

C3	**Cost**	6	6	3
C4	**Compliance with the available schedule**	7	7	6
C5	**Flight safety**	1	1	2
C6	**Flight security**	2	2	4
C7	**Passenger satisfaction**	3	3	5

Using the equations 1 to 10 given in the method section, lower and upper limits of $RN(C_j)$ values, normalized $RN(S_j)$ values, $RN(K_j)$ coefficient values, $RN(Q_j)$ recalculated weight values, are indicated in the Table 4. On the other hand, lower and upper limits of $RN(K_j)$ final weight values as well as the crisp values of the final weights are given in the Table 5.

Table 4. Lower and upper limits of $RN(C_j)$, $RN(S_j)$, $RN(K_j)$ and $RN(Q_j)$ values of the criteria

Criteria	C lower	C upper	S lower	S upper	K lower	K upper	Q lower	Q upper
C5	1,111	1,556	1,000	1,000	1,000	1,000	1,000	1,000
C6	2,222	3,111	0,323	0,483	1,323	1,483	0,674	0,756
C7	3,222	4,111	0,468	0,638	1,468	1,638	0,412	0,515
C2	2,333	3,667	0,339	0,569	1,339	1,569	0,262	0,385
C1	5,222	6,111	0,758	0,948	1,758	1,948	0,135	0,219
C3	4,333	5,667	0,629	0,879	1,629	1,879	0,072	0,134
C4	6,444	6,889	0,935	1,069	1,935	2,069	0,035	0,069

Table 5. Final weight values of the criteria

Criteria	W lower	W upper	Final crisp weight value
C5 – Flight safety	0,325	0,386	**0,355**
C6 – Flight security	0,219	0,292	**0,256**
C7 – Passenger satisfaction	0,134	0,199	**0,166**
C2 – Punctuality/time	0,085	0,149	**0,117**
C1 – Environmental impact	0,044	0,085	**0,064**
C3 – Cost	0,023	0,052	**0,038**
C4 – Compliance with the available schedule	0,011	0,027	**0,019**

According to Table 5, Flight safety is deemed the most important criterion by the DMs with 35.5% weight. It is followed by flight security (25.6%), passenger satisfaction (16.6%), punctuality/time (11.7%), environmental impact (6.4%), cost (3.8%), and compliance with the available schedule (1.9%) respectively. The importance levels of the criteria are illustrated in Figure 1.

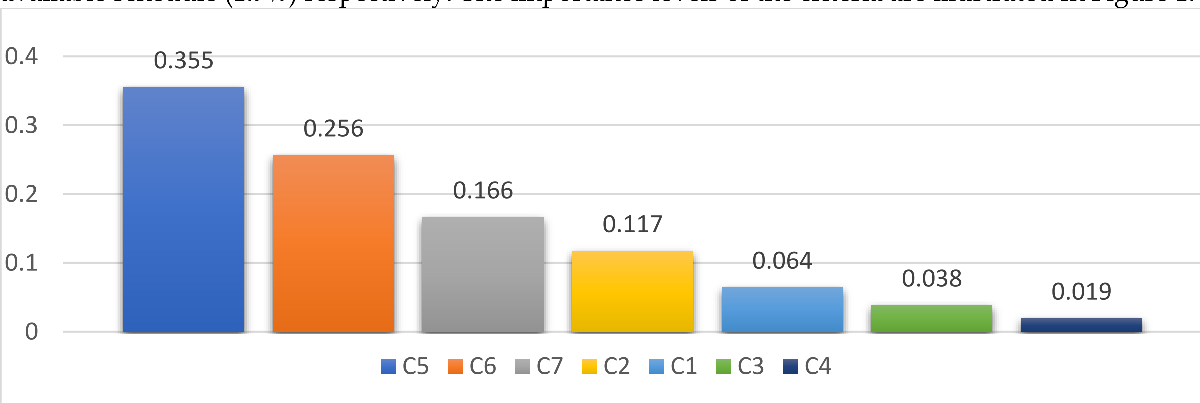

Figure 1. Importance levels of the airline disruption management criteria

4. Conclusion, Discussion and Suggestion

This study was conducted to understand and reveal the criteria that are effective in choosing airline disruption management responses. The findings reveal that flight safety is by far the most important criterion in the decision making of airlines' disruption management processes. As safety requirements and regulations are strict in aviation business, each disruption management response is expected to abide by the "safety comes first" principle. As also noted by Su et al. (2021), in times of severe weather conditions or high congestion, diverting to alternative airports or holding at apron may be the safest option despite bringing extra costs. Furthermore, safety of flight is the most important criterion among International Air Transport Association (IATA)'s diversion management criteria (Marzuoli et al., 2016). The safety of flight includes selecting the nearest suitable emergency airport, evaluating the remaining fuel and approving the alternate airport. Security is also another notable criterion being the second most important one in the present study. Despite a lack of multi criteria research in airline disruption management, security is one of the factors considered in disruption management applications. For example, in their concluding remarks, Sousa et al. (2015) expressed the need to check if a new disruption management model in aircraft assignments take into consideration if it compromise security protocols. Since disruptions may create tough working environment and lead to unruly passenger behavior, security must also be considered in the disruption management process.

Passenger satisfaction is another important facet which needs to be managed effectively in times of disruption. Herein, passenger recovery is focusing on reducing delay time and compensating the reduced passenger satisfaction in a disruption event (Maher, 2015). Passenger satisfaction has the potential to attract passengers in the long term and is found the third most important criterion in this study. Sustained passenger dissatisfaction may harm the brand image of airlines, and lead to customer complaints as noted by (Efthymiou et al., 2018). Punctuality/time is at the core of the airline disruption management. However, in this study, it is positioned at medium level of importance as it may be interrelated by DMs with criteria such as passenger satisfaction and cost. Despite we found environmental impact as fifth important criterion, environmental implications of operational decisions will more likely to be an important constraint in any disruption management process. Environmental criteria can become the main topic in cruise speed alterations. Parallel to this notion, Aktürk et al. (2014) integrated environmental cost and constraints next to the additional fuel cost of speeding up flights in their exact optimization method. Cost on the other hand, is surprisingly found the sixth important criterion based on DMs perspectives. Due to the fact that airlines are profit oriented entities such as every enterprise, the cost may be thought to be at higher ranking. This may result from the fact that DMs whom we interviewed were not employed in a low cost carrier. However, cost is used as one of the objective function variables in many assignment problems (Clausen et al., 2010; Liu et al., 2008; Su et al., 2021). The cost can be in various forms such as compensation cost, crew cost, cancellation cost, etc. It is possible to obtain different results when conducting the interviews with experts working in different airlines. Moreover, compliance with the available schedule is found the least important criterion in this study. Normally, it is important that delayed flights do not affect other flights, crews, or passengers in a chain effect. However, in this study, it was found to be of lower importance compared to other criteria. During a disruption, full compliance with the existing schedule is often difficult to achieve and is not considered a realistic goal. Therefore, this criterion may have naturally been ranked lower by DMs. Another contributing factor of this finding could be that the interviews were made with employees of charter airlines which has potentially less affected network structure in times of disruptions. In the criteria construction phase, integrating the data from experts working in airlines with different business models by interviewing a more diverse group of experts could yield more comprehensive results.

Disruption management is a difficult task as the total cost of each operation include many dependent factors, e.g., to cancel a flight one must consider the cost of parking in a certain airport, the hotel charges for both crew and passengers and the cost of alternative transportation for passengers. Accordingly, decision support systems play a major role in aiding operational control centers of airlines. Focusing on the disruption management criteria, this study can provide fundamental perspective for such systems and models with multi criteria decision making approach. Since such decision making methods are not well established in the airline disruption management literature, the present paper can pave the wave for more detailed decision making analysis.

Operational decisions against disruptions can be affected by numerous factors from environmental effects to time management, costs, safety, security, and passenger satisfaction as already outlined in this study. In this regard, experience, and quick decision-making abilities of aviation personnel are of paramount importance with their capabilities to handle disruptions. For example, effective communication and coordination among employees can play a key role in enhancing passenger satisfaction when a disruption response diminishes passenger satisfaction which is one of the criteria discussed in this paper. Additionally, as suggested by Geske et al. (2024), use of artificial intelligence based collaborative decision making could provide optimum solution to encountered disruptions by guiding aviation professionals.

5. Limitations

This study is not exempt from limitations. Firstly, we did not create wholesome criteria with sub-criteria. Secondly, we only performed calculation of weights. Because it is not possible to create certain set of alternatives (airline disruption management responses in this case) for general use, and since disruption responses are event-specific, we only performed calculation of weights. Further studies can use specific scenarios or real life examples which may allow DMs to evaluate alternatives based on the criteria. Finally, it can be expected that the study can be conducted with a larger number of experts to cover detailed perspectives from various airlines with different business models, who share same working environment, such as a specific airport.

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