



AIRLINES' OPERATIONAL RESILIENCE ASSESSMENT: INTEGRATING BWM, TODIM, AND ROUGH DOMBI METHODS

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Article History:

- received 24 March 2025
- accepted 19 June 2026
- first published online 29 September 2026

Abstract. The aviation sector is among the most vulnerable industries to unforeseen disruptions, including natural disasters, pandemics, and international conflicts. Airlines are increasingly recognizing the critical importance of business resilience in managing these disruptions. This study develops a comprehensive framework that utilizes Rough Dombi and Z-number fuzzy methodologies, combined with multi-criteria decision-making (MCDM) approaches, to evaluate criteria and solutions influencing aviation industry resilience in Taiwan through a case study of four airlines. First, an evaluation framework for airline resilience is established through a literature review and expert interviews. The Best-Worst Method (BWM) determines the weights of evaluation indicators, while the TODIM (Tomada de Decisão Interativa Multicritério) method identifies gaps between each company's performance and ideal values. Results reveal that "Management expertise sensitive to environmental changes and able to enhance abilities beyond their own business" is the most influential factor, and Airline A₂ serves as a benchmark for others. Sensitivity analysis with varying criterion weights and comparative analysis with alternative MCDM techniques validate the robustness and reliability of the findings.

Keywords: resilience, rough Z-numbers, DOMBI, BWM, TODIM.

JEL Classification: C43, C61, D81.

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1. Introduction

Global crises and supply chain disruptions have forced many companies to modify their strategic goals from profit maximization to resilience planning (Kou et al., 2022). The COVID-19 pandemic has had a more severe impact on aviation travel than past disasters. Governments worldwide have implemented social distancing measures to reduce disease transmission, severely harming the travel industry, particularly the airline sector. Passenger services were among the hardest-hit industries, with capacity significantly limited. Travel restrictions, overseas travel bans, and quarantine protocols led businesses to reduce their operations by 60% (Fan et al., 2024). This has made resilience a central component of business risk management. Minciu et al. (2025) defined resilience as a corporation or business entity's ability to manage disruptive changes during crises, implement effective pre-disaster preventive measures, respond rapidly and effectively to disaster impacts, and recover critical services adaptively. Organizational resilience is the ability to adapt, recover, and thrive in the face of uncertainty,

challenges, and change. This resilience goes beyond resistance to negative repercussions, demonstrating the organization's adaptability and strength. Resilient organizations can weather market shifts, economic fluctuations, and other external shocks (Xu et al., 2024).

Corporate resilience is constructed upon multiple levels, from organizational culture to business processes and technology infrastructure. On the cultural level, resilience means having an open culture of communication and collaboration that allows for rapid learning and adaptation to changing circumstances. In terms of business processes, enterprises need to develop flexible operating models that allow them to adjust strategies and reconfigure resources quickly. Meanwhile, the technology infrastructure enables the scalability and stability of the system, ensuring reliable service even under pressure (Shi et al., 2022). In recent years, many studies have applied Multiple Criteria Decision Making (MCDM) methods to quantify corporate resilience. For example, Zarei et al. (2021) developed a fuzzy hybrid multi-criteria decision-making model that utilizes the Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy VIKOR (F-VIKOR) techniques to quantify and evaluate corporate resilience in factories. Ayyildiz et al. (2023) proposed a hybrid decision-making method that combines the BWM and Interval-valued Intuitionistic Fuzzy AHP to understand and rank the impact of reliability, flexibility, responsiveness, costs, and assets on green supply chain resilience under COVID-19. Meanwhile, Mohammed et al. (2021) employed the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to assess the relative importance of six criteria, aiming to establish a resilient supply chain. These six resilience criteria included flexibility, agility, redundant suppliers, risk oversight, cooperation, and visibility, with flexibility receiving the highest relative weight ranking. Subsequently, they applied their hybrid MOTV method (MABAC-OCRA-TOPSIS-VIKOR) to verify the supplier rankings. A literature review revealed a limited body of academic research on airline business operations and crisis management during catastrophic disasters. Few studies have examined airline firm resilience or built evaluation frameworks for aviation sector management decision-making. This study creates an airline resilience framework and multi-criteria decision-making model to analyze airline resilience.

The evaluation of resilience in the aviation industry is an MCDM problem, and determining the criteria weights is one of the key issues. Each of the commonly used methods for obtaining criteria weights, such as AHP (Darko et al., 2019), DEMATEL (Yazdi et al., 2020), BWM (Gupta, 2018), FUCOM (Pamučar et al., 2018), and SWARA (Keršulienė et al., 2010), has its own advantages and disadvantages. Although the traditional AHP method is often applied, it requires $n(n - 1)/2$ pairwise comparisons, making it complex in situations with numerous criteria. In contrast, the BWM method does not require the ranking of all criteria, which makes evaluation easier, reduces inconsistent results, and lessens the required number of pairwise comparisons to $(2n - 3)$. Various researchers have employed BWM to analyze different topics. For instance, Rezaei (2024) utilized the BWM to integrate, evaluate, and classify current research directions, simultaneously identifying gaps in research within the field of multi-criteria decision making (MCDM), especially concerning the diverse applications of BWM in supply chain management, energy, sustainability, and technological innovation. Zeng et al. (2023) employed the fuzzy BWM for selecting green-resilient suppliers within the framework of supply chain management (SCM), highlighting supplier sustainability and resilience as critical elements for sustaining system performance and adaptability. López et al. (2022) employed

the Calibrated Fuzzy BWM to evaluate and enhance supply chain resilience in the face of global disruptions induced by the COVID-19 pandemic. From the viewpoint of an emerging economy, Yaran Ögel et al. (2022) utilized the fuzzy Dombi-Bonferroni Best-Worst (DB-FBWM) technique to determine and rank the factors contributing to retail food waste. Therefore, the BWM method is adopted in this study to examine the weight of criteria.

For selecting or ranking solutions there are various methods such as TOPSIS (Sun, 2010), MABAC (Multi-Attributive Border approximation Area Comparison) (Pamučar & Božanić, 2019), VIKOR (Mateusz et al., 2018), ELECTRE (Yu et al., 2018), PROMETHEE II (Preference Ranking Organization Method for Enrichment of Evaluation II) (Tian et al., 2020), SECA (Simultaneous Evaluation of Criteria and Alternatives) (Bahrami & Rastegar, 2022), and EDAS (Evaluation based on Distance from Average Solution) (Keshavarz Ghorabae et al., 2017). However, none of the above methods considers the psychological behavior of the experts (Zhang et al., 2023). When faced with uncertain environments, experts are assumed to be boundedly rational rather than entirely rational (Li et al., 2019). Psychological factors influence experts' decision outcomes (Zhang et al., 2023), making it crucial to consider their psychological characteristics. The Tomada de Decisão Interativa Multicritério (TODIM) is an effective method, based on prospect theory, that captures experts' psychological behavior and does not require prior knowledge of aspiration levels for the attributes (Tian et al., 2021; Zhao et al., 2022). Therefore, the TODIM method is applied in this study to rank the alternatives.

Aviation operational resilience is a safety-critical, failure-sensitive system in which a single vulnerability can lead to cascading failures. As a result, aggregation must support regulated partial compensation rather than basic risk averaging. The Dombi operator is particularly suited to this application since its parameter allows for variable sensitivity to weak criteria while maintaining appropriate t-norm/t-conorm features (Dombi, 1982). Smaller λ values allow for more compensatory behavior, but larger λ values demand stricter, nearly non-compensatory aggregation, which aligns with the sensitivity needs of complex resilience systems. Although the Einstein norm is commonly used in MCDM research, it is not parametric and hence lacks the flexibility needed to simulate compensating behavior. Furthermore, Einstein aggregation smooths extreme numbers, which may underestimate crucial low-performance hazards. The Frank (Frank, 1979) norm, although parametric, adjusts only global compensation through a log-exponential smoothing mechanism, reducing sensitivity to extremely low values. Similarly, the Aczél–Alsina (Aczél & Alsina, 1982) norm is inherently non-compensatory due to its generator $g(x) = (-\ln x)^\phi$, which amplifies low values and enforces a weakest-link logic. Consequently, Dombi aggregation provides the most appropriate balance between sensitivity and controlled compensation for modeling airline operational resilience.

However, as an operator, DOMBI cannot address the ambiguity inherent in processing expert opinion data, which exhibits uncertainty and inconsistency due to variations in expert knowledge, experience, and information interpretation. To resolve this issue, the study suggests combining Rough Set Theory (Pawlak, 1982) with the DOMBI synthesis operator (Dombi, 1982; Chen & Ye, 2017) within the context of imprecise MCDM based on Z-numbers (Zadeh, 2011). In this methodology, Rough Set Theory addresses ambiguity and indistinguishability through the application of lower and upper approximations, thereby delineating definitive and potential information. Meanwhile, the DOMBI operator, a parameterized

t-norm/t-conorm, enables precise modulation of the compensation degree and sensitivity among criteria via control parameters, facilitating an accurate representation of nonlinear interactions. Compared to linear synthesis approaches such as SAW or Bonferroni, Rough Dombi more accurately captures the compensation mechanism between prominent and less significant criteria and demonstrates effective performance with raw data represented as value ranges. Finally, the Z-number introduces an additional dimension to represent the reliability of ambiguous information, aligning with the way humans evaluate data under conditions of uncertainty. Integrating Rough Set, Dombi, and Z-number methodologies establishes a comprehensive MCDM framework, enabling the concurrent management of uncertainty, volatility, reliability, and interrelationships among criteria in evaluating the operational resilience of airlines.

This study contributes the following: (1) The aviation industry resilience framework was created for the first time after examining the literature and expert perspectives; (2) The proposed MCDM method in this research enhances previous methodologies for assessment utilizing the aviation sector resilience framework, addressing numerous inadequacies; (3) The strengths and weaknesses of each airline can be identified through empirical analysis. This method also highlights the gap between the current and ideal values for each criterion for each airline, providing decision-makers with a reference for strengthening aviation industry resilience and suggesting specific areas for improvement.

2. Literature review

This section comprises four subsections: airline resilience development, resilience evaluation indicators, detailed explanations, and related studies.

2.1. Challenges facing the airline industry

The airline industry has faced unprecedented challenges in recent years due to the COVID-19 pandemic. Global travel restrictions and widespread health issues have caused numerous problems, resulting in substantial economic losses for the sector. Many airlines had to cancel or reduce flights due to declining passenger demand, resulting in significant revenue losses. Airlines faced severe financial difficulties, requiring government aid or cost-cutting measures (Migdadi, 2022). The pandemic also harmed aviation workers. Flight suspensions and reductions forced many airlines to lay off staff, including pilots, flight attendants, and ground crew (Sobieralski, 2020). Furthermore, airline operations have become more susceptible to interruptions produced by both internal and external forces. Adverse weather conditions, strikes, political reasons, aircraft mechanical difficulties, crew sickness, and other varied causes can damage an airline's long-term profitability by generating flight interruptions and breaking operational consistency (Bülbül, 2022). Although aviation has returned to pre-pandemic levels in recent years, the industry has recognized that profitability alone is insufficient to navigate the unpredictable future market. To handle future crises, companies must strengthen resilience by examining operational systems, processes, and organizational structures, and actively seeking new business models.

2.2. Theories background

Holling (1973) was the first to establish the concept of resilience 1973. According to Holling (1973), resilience is the magnitude of the stable zone around time-invariant equilibrium points (gravitational points) or stable oscillations (periodic gravitational points) in ecosystems. This term has been used in engineering, psychology, economics, strategic management, supply chain management, and transportation (Bhamra et al., 2011; Wan et al., 2018), focusing on an individual or organization's ability to recover from disruption and continue operations. Carpenter et al. (2001) define resilience as a system's ability to absorb disturbances while maintaining structural and functional integrity, self-organize without external intervention, and learn and adapt to disruptions. Organizations and communities are dynamic, complex systems with interdependent parts. Complex systems require high levels of resilience, which is challenging to achieve. According to Ponomarov and Holcomb (2009), preparedness, response, and recovery or adjustment are the resilience stages. As globalization complicates systems, resilience-enhancing methods must be developed and implemented to address these complexities. Consider each resilience level and its relationships.

Operational resilience is defined as an organization's capacity to prevent disruptions while maintaining the ability to rapidly adjust and recover from adverse events, thereby enabling goal achievement even under challenging conditions (Stolker et al., 2008). When organizations fail to restore normal operations following a disruption, they demonstrate a fundamental lack of operational resilience (Allen & Davis, 2010). As a multifaceted construct, operational resilience encompasses both disturbance absorption and recovery capabilities, with each component contributing to enhanced organizational performance across varying types and magnitudes of interruptions (Essuman et al., 2020). While disruption absorption requires redundant systems and buffering capacity, the recovery dimension emphasizes organizational adaptability and flexibility. However, building operational resilience entails high costs (Essuman et al., 2020), necessitating careful consideration of the trade-offs between resilience investments and anticipated returns. In contexts characterized by minimal operational disruption risk, excessive investment in resilience measures may prove economically inefficient. Achieving superior operational performance requires a comprehensive understanding of operational resilience and its behavioral dynamics. Organizations seeking competitive advantage must therefore articulate their operational procedures explicitly and systematically identify their resilience requirements based on their specific risk profiles and operational contexts.

2.3. Importance of corporate resilience in the airline industry

Air transport is a vital component of global commerce and travel, as it facilitates swift and efficient international transportation. The air transportation system is similarly multi-tiered, with nodes belonging to multiple tiers simultaneously, a characteristic shared with comparable real-world systems (Cardillo et al., 2013). Flight operations are carried out by airports, passengers, and flight crews. These are the most visible components of the air transportation system, which includes numerous more sub-elements (Ball et al., 2007). Due to the increasing complexity and volatility in global systems, air travel, arguably more than other modes of transportation, is susceptible to a wide range of disruptions. Aside from minor disruptions,

terrorist attacks, epidemics, natural disasters, economic downturns, strikes, human error, equipment failures, crew illnesses, and a variety of other causes all pose serious threats to airline operations (Jimenez Serrano & Kazda, 2017). Based on the theory's background, this study combines features of airline operations with resilience evaluation factors to create a six-dimensional framework for airline resilience.

Sustainability: Sustainability refers to the aviation industry's potential to achieve long-term economic, social, and environmental sustainability through improved efficiency, responsible financial management, and beneficial societal effects (Wang et al., 2024).

Robustness: Robustness refers to an aviation system's ability to remain stable and operate safely and continuously in the face of unforeseen interruptions, such as disasters, accidents, or pandemics (Hsu et al., 2022).

Flexibility: Flexibility refers to the ability to quickly modify activities, such as flight scheduling and resource allocation, in response to shifting demand, environmental circumstances, and emergencies (Ayyildiz et al., 2023; Zarei et al., 2021).

Awareness: Awareness refers to the ability to continuously monitor operational circumstances, identify dangers, and adapt quickly to environmental, technical, and regulatory changes (Zarei et al., 2021).

Corporate Strategy: Corporate strategy is defined as the long-term planning and strategic efforts that align resources, technology, and market positioning to generate a sustained competitive advantage in dynamic environments (Belhadi et al., 2021; Serfontein & Govender, 2021).

Financial Ability: Financial ability refers to competent financial management and liquidity capacity that allow airlines to invest, maintain stability, and absorb operational shocks in a capital-intensive industry (Belhadi et al., 2021).

2.4. Applications of MCDM in the airline industry

The airline industry presents a multi-criteria decision-making (MCDM) challenge due to its complex nature, involving numerous factors and stakeholders. Many studies have successfully applied MCDM combinations to airline resilience research. For example, Tanrıverdi et al. (2022) employed the Dombi–Bonferroni BWM model to assess and determine the significance of factors influencing airport selection by air carriers during the COVID-19 pandemic. To assess and select sustainable aviation fuel (SAF) suppliers for airlines, Ecer et al. (2025) implemented the LOPCOW and MARCOS methodologies combined with interval-valued fuzzy neutrosophic information. Lee et al. (2018) utilized the MCDM methodology, incorporating DEMATEL, Analytic Network Process (ANP), and Zero-One Goal Programming (ZOGP), to identify the optimal green aviation fleet management strategy supporting the aviation sector's aim to enhance corporate social responsibility (CSR) and environmental conservation to alleviate the impacts of climate change, despite multidimensional resource constraints. Markatos et al. (2023) employed a hybrid MCDM approach to assess the sustainability of aerospace materials, emphasizing sensitivity analysis to evaluate the robustness and reliability of the MCDM tool, with a focus on sustainability and a circular economy within the aerospace industry. Markatos and Pantelakis (2023) employed a holistic MCDM method in conjunction with AHP and a weighted addition model to evaluate and compare commercial aircraft types

based on sustainability criteria, factoring in economic costs, ecological impacts, and technological factors in the context of the aviation industry's pursuit of sustainable development and a circular economy.

3. Research methodology

This section introduces the MCDM method applied in this study and provides a detailed description of each step. Figure 1 illustrates the research flow chart, which consists of two stages.

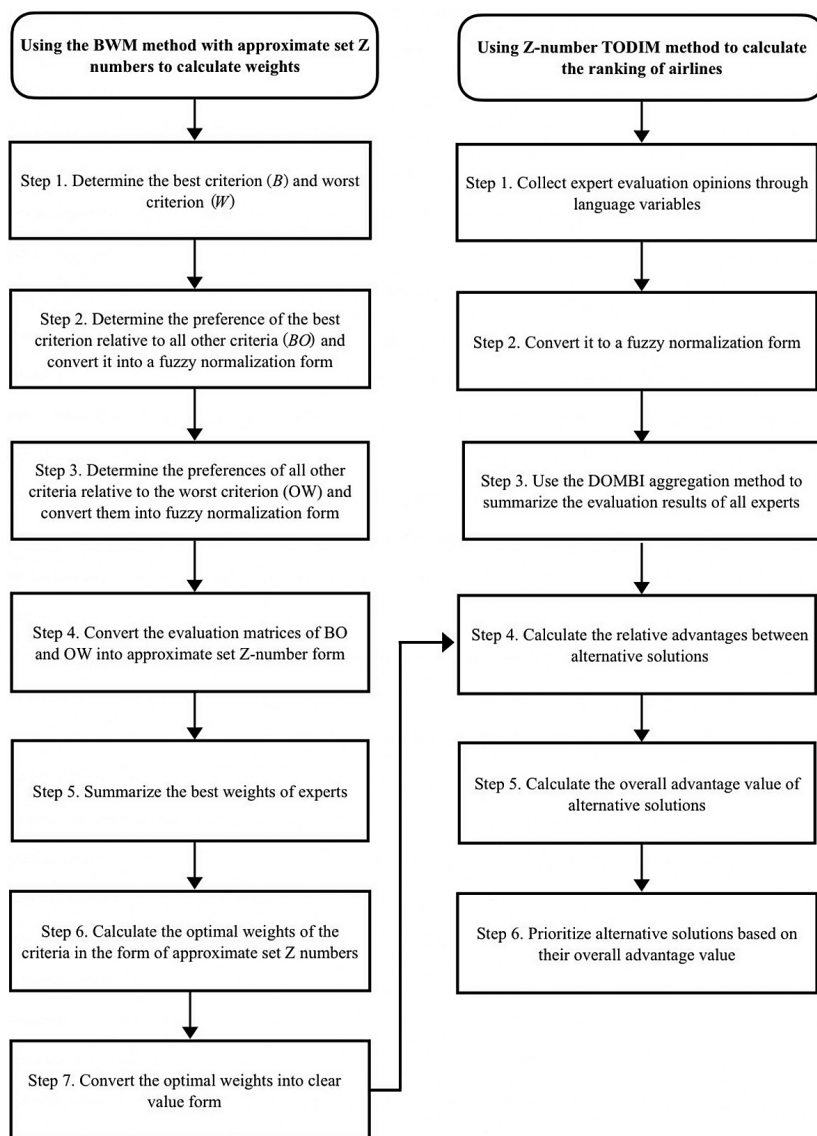


Figure 1. Flow chart of research methodology

Stage 1: The BWM approach and rough Z-number representation were employed to estimate the weighting of assessment criteria. Experts identified the best and worst criteria and prioritized them accordingly. Normalizing and converting these judgments to Z-numbers to reflect expert opinion uncertainty helped synthesize and determine criterion weights.

Stage 2: The Z-number-based TODIM ranked airlines based on their operational resilience. Expert ratings, expressed as linguistic variables to capture the experts' uncertain judgments, were synthesized using the Dombi operator. TODIM calculated the relative benefit of the alternatives based on the weights established in the first phase, providing the overall advantage value and ranking the airlines accordingly.

3.1. The BWM method for rough Z numbers

The revised BWM approach, which utilizes rough Z values to convey information, is described below. Based on the original BWM approach, the framework has been modified to include approximate set Z numbers. We use an evaluation matrix of rough Z numbers and output weights in the same format. The weights will be translated into values to show the relative relevance of the criteria.

Step 1. Determine the best (B) and worst criterion (W)

Take a decision-making system with experts $e(e=1,2,\dots,s)$. Experts select B and W to obtain B^e and W^e .

Step 2. Assess preference ratings by comparatively evaluating the optimal criterion against all remaining criteria (BO), subsequently transforming the assessments into fuzzy normalized forms via established semantic measures (Tables 1 and 2).

Table 1. Linguistic variables indicating importance and their corresponding fuzzy numbers

Linguistic variables	Corresponding fuzzy numbers
Equally Important (EI)	(1, 1, 3)
Weakly Important (WI)	(1, 3, 5)
Fairly Important (FI)	(3, 5, 7)
Very Important (VI)	(5, 7, 9)
Absolutely Important (AI)	(7, 9, 9)

Table 2. Linguistic variables for reliability and their corresponding fuzzy numbers

Linguistic variables	Corresponding fuzzy numbers
Very Low (VL)	(0.0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.5, 0.7, 0.9)
Very High (VH)	(0.7, 0.9, 1.0)

The first-step linguistic Z number can be normalized in a form $Z_{Bk}^e = (z_{Bk}^{el}, z_{Bk}^{em}, z_{Bk}^{eu})$. The best criterion's assessment matrix compared to all others (BO) is represented by V_{BO} as follows:

$$V_{BO} = \begin{pmatrix} Z_{B1}^1 & \cdots & Z_{Bn}^1 \\ \vdots & \ddots & \vdots \\ Z_{B1}^s & \cdots & Z_{Bn}^s \end{pmatrix}. \quad (1)$$

Step 3. Fuzzy normalize all other criteria' preferences relative to the worst criterion (OW).

Similarly, the preferences of all other criteria for the worst criterion W^e can be represented by $Z_{kW}^e = (z_{kW}^{el}, z_{kW}^{em}, z_{kW}^{eu})$.

The evaluation matrix of all other criteria relative to the worst criterion (OW) is represented by V_{OW} as follows:

$$V_{OW} = \begin{pmatrix} Z_{1W}^1 & \cdots & Z_{nW}^1 \\ \vdots & \ddots & \vdots \\ Z_{1W}^s & \cdots & Z_{nW}^s \end{pmatrix}. \quad (2)$$

Step 4. Convert the BO and OW evaluation matrices into rough Z-numbers.

Set Z numbers can approximate regular fuzzy numbers from step 2. Matrices V_{BO} and V_{OW} are converted into matrices $RZ(V_{BO})$ and $RZ(V_{OW})$, in rough Z number:

$$\begin{aligned} RZ(V_{BO}) &= \begin{pmatrix} RZ(Z_{B1}^1) & \cdots & RZ(Z_{Bn}^1) \\ \vdots & \ddots & \vdots \\ RZ(Z_{B1}^s) & \cdots & RZ(Z_{Bn}^s) \end{pmatrix}, \\ RZ(V_{OW}) &= \begin{pmatrix} RZ(Z_{1W}^1) & \cdots & RZ(Z_{nW}^1) \\ \vdots & \ddots & \vdots \\ RZ(Z_{1W}^s) & \cdots & RZ(Z_{nW}^s) \end{pmatrix}. \end{aligned} \quad (3)$$

Step 5. Summarize the best weights given by the experts

By using the Dombi method, the optimal weights of s experts can be aggregated:

$$\begin{aligned} RZ(w_k^*) &= ([w_k^{*lL}, w_k^{*lU}], [w_k^{*mL}, w_k^{*mU}], [w_k^{*uL}, w_k^{*uU}]) = \\ &= \left[\frac{\sum_{e=1}^s w_k^{el*}}{1 + \left\{ \sum_{e=1}^s w_j \left(\frac{1 - f(w_{(\varphi_j)}^{el})}{f(w_{(\varphi_j)}^{el})} \right)^{\rho} \right\}^{\frac{1}{\rho}}}, \frac{\sum_{e=1}^s w_k^{eu*}}{1 + \left\{ \sum_{e=1}^s w_j \left(\frac{1 - f(w_{(\varphi_j)}^{eu})}{f(w_{(\varphi_j)}^{eu})} \right)^{\rho} \right\}^{\frac{1}{\rho}}} \right], \end{aligned} \quad (4)$$

where

$$f(w_{(\varphi_j)}) = \begin{cases} f(w_{(\varphi_j)}^{el}) = \frac{w_{(\varphi_j)}^{el}}{\sum_{j=1}^n w_{(\varphi_j)}^{el}} \\ f(w_{(\varphi_j)}^{eu}) = \frac{w_{(\varphi_j)}^{eu}}{\sum_{j=1}^n w_{(\varphi_j)}^{eu}} \end{cases}. \quad (5)$$

Step 6. Determine the best criteria weights as rough Z values.

The optimal criteria weights are obtained by solving the following optimization model, which expands the rough Z-number relationships into their corresponding lower, middle, and upper bounds to ensure computational feasibility with the best consistency ξ^e :

$$\begin{aligned}
 & \min \xi^e \\
 & \text{s.t.} \\
 & \left| \frac{w_B^{eLL}}{w_k^{euU}} - Z_{Bk}^{eLL} \right| \leq \xi^e, \left| \frac{w_B^{eLU}}{w_k^{euL}} - Z_{Bk}^{eLU} \right| \leq \xi^e, \\
 & \left| \frac{w_B^{emL}}{w_k^{emU}} - Z_{Bk}^{emL} \right| \leq \xi^e, \left| \frac{w_B^{emU}}{w_k^{emL}} - Z_{Bk}^{emU} \right| \leq \xi^e, \\
 & \left| \frac{w_B^{euL}}{w_k^{euU}} - Z_{Bk}^{euL} \right| \leq \xi^e, \left| \frac{w_B^{euU}}{w_k^{euL}} - Z_{Bk}^{euU} \right| \leq \xi^e, \\
 & \left| \frac{w_k^{eLL}}{w_W^{euU}} - Z_{kW}^{eLL} \right| \leq \xi^e, \left| \frac{w_k^{eLU}}{w_W^{euL}} - Z_{kW}^{eLU} \right| \leq \xi^e, \\
 & \left| \frac{w_k^{emL}}{w_W^{emU}} - Z_{kW}^{emL} \right| \leq \xi^e, \left| \frac{w_k^{emU}}{w_W^{emL}} - Z_{kW}^{emU} \right| \leq \xi^e, \\
 & \left| \frac{w_k^{euL}}{w_W^{euU}} - Z_{kW}^{euL} \right| \leq \xi^e, \left| \frac{w_k^{euU}}{w_W^{euL}} - Z_{kW}^{euU} \right| \leq \xi^e, \\
 & w_k^{eLL} \leq w_k^{emL} \leq w_k^{euL}, k = 1, 2, \dots, n, \\
 & w_k^{eLU} \leq w_k^{emU} \leq w_k^{euU}, k = 1, 2, \dots, n, \\
 & w_k^{eLL} \leq w_k^{eLU}, w_k^{emL} \leq w_k^{emU}, w_k^{euL} \leq w_k^{euU}, k = 1, 2, \dots, n, \\
 & \sum_{k=1}^n \frac{(w_k^{eLL} + w_k^{emL} + w_k^{euL})}{6} \leq 1, \\
 & \sum_{k=1}^n \frac{(w_k^{eLU} + w_k^{emU} + w_k^{euU})}{6} \geq 1, \\
 & w_k^{eLL} \geq 0, k = 1, 2, \dots, n.
 \end{aligned} \tag{6}$$

Step 7. Convert the optimal weights into crisp values.

Best Weight: $RZ(w_k^*) = ([w_k^{*LL}, w_k^{*LU}], [w_k^{*mL}, w_k^{*mU}], [w_k^{*uL}, w_k^{*uU}])$ can be converted into fuzzy number form as follows:

$$w_k^l = \frac{\varphi_k^l}{\sum_{k=1}^n \varphi_k^l}, \tag{7}$$

where

$$\begin{aligned}
 \varphi_k^l &= \min_k \{w_k^{*LL}\} + \chi_k^l \times (\max_k \{w_k^{*LU}\} - \min_k \{w_k^{*LL}\}), \\
 \chi_k^l &= \frac{w_k^{*LL} \times (1 - w_k^{*LU}) + w_k^{*LU} \times w_k^{*LL}}{1 - w_k^{*LU} + w_k^{*LL}},
 \end{aligned}$$

$$\begin{aligned} w_k^{*IL} &= \frac{w_k^{*IU} - \min_k \{w_k^{*IL}\}}{\max_k \{w_k^{*IU}\} - \min_k \{w_k^{*IL}\}}, \\ w_k^{*IU} &= \frac{w_k^{*IU} - \min_k \{w_k^{*IU}\}}{\max_k \{w_k^{*IU}\} - \min_k \{w_k^{*IL}\}}. \end{aligned} \quad (8)$$

Similarly, w_k^m and w_k^u can be obtained from Eq. (8). Alternatively, clear weight values can be obtained through the following method:

$$w_k = \frac{w_k^l + 4w_k^m + w_k^u}{6}. \quad (9)$$

3.2. TODIM method for Z-numbers

This section covers the Z-number-based enhanced TODIM approach. The TODIM technique is modified to use Z-numbers. Expert evaluation opinions are collected using linguistic factors and turned into Z-numbers. The distance formula and Z-number expectation are used to accurately compare and quantify Z-value differences, evaluating the relative advantage of various solutions. The total advantage is calculated from the relative advantage and used to rate different solutions.

Step 1. Collect the expert evaluation opinions expressed as linguistic variables

Each expert evaluates the performance of each alternative A_i on criterion C_k using the predefined semantic scales for performance levels (Table 3) and reliability (Table 2).

Table 3. Linguistic variables and corresponding fuzzy numbers for performance evaluation

Linguistic variables	Corresponding fuzzy numbers
Very Poor (VP)	(0.0, 0.0, 0.1)
Medium Poor (MP)	(0.0, 0.1, 0.3)
Poor (P)	(0.1, 0.3, 0.5)
Fair (F)	(0.3, 0.5, 0.7)
Good (G)	(0.5, 0.7, 0.9)
Medium Good (MD)	(0.7, 0.9, 1.0)
Very Good (VG)	(0.9, 1.0, 1.0)

The linguistic Z number obtained from the first step can be converted into a regular fuzzy number. a_{ik}^e . The performance matrix A^e of the alternative solutions is as follows:

$$A^e = \begin{pmatrix} a_{11}^e & \cdots & a_{1n}^e \\ \vdots & \ddots & \vdots \\ a_{m1}^e & \cdots & a_{mn}^e \end{pmatrix}. \quad (10)$$

Step 2. Summarize the evaluation results of all experts

The Dombi method is applied to aggregate the experts' opinions to obtain a comprehensive evaluation matrix:

$$ZTODIM\{ZN_{(\varphi_1)}, ZN_{(\varphi_2)}, \dots, ZN_{(\varphi_n)}\} = \left[\frac{\sum_{e=i}^s z_{(\varphi_j)}^{el}}{1 + \left[\sum_{e=1}^s w_j \left(\frac{1 - f(z_{(\varphi_j)}^{el})}{f(z_{(\varphi_j)}^{el})} \right)^\rho \right]^{\frac{1}{\rho}}}, \frac{\sum_{e=i}^s z_{(\varphi_j)}^{eu}}{1 + \left[\sum_{e=1}^s w_j \left(\frac{1 - f(z_{(\varphi_j)}^{eu})}{f(z_{(\varphi_j)}^{eu})} \right)^\rho \right]^{\frac{1}{\rho}}} \right], \quad (11)$$

wherein

$$f(z_{(\varphi_j)}) = \begin{cases} f(z_{(\varphi_j)}^{el}) = \frac{z_{(\varphi_j)}^{el}}{\sum_{j=1}^n z_{(\varphi_j)}^{el}}, \\ f(z_{(\varphi_j)}^{eu}) = \frac{z_{(\varphi_j)}^{eu}}{\sum_{j=1}^n z_{(\varphi_j)}^{eu}} \end{cases}, \text{ and } ZD(A^e) = \begin{pmatrix} ZD(a_{11}) & \dots & ZD(a_{1n}) \\ \vdots & \ddots & \vdots \\ ZD(a_{m1}) & \dots & ZD(a_{mn}) \end{pmatrix}. \quad (12)$$

Step 3. Calculate the relative advantages of alternative solutions

The relative dominance of alternative A_i to A_j is computed as:

$$\varsigma(A_i, A_j) = \sum_{k=1}^n \phi_k(A_i, A_j), \quad (13)$$

where $\phi_k(A_i, A_j)$ denotes the dominance function of the criterion C_k , defined as:

$$\phi_k(A_i, A_j) = \begin{cases} \sqrt{\frac{w_k}{\sum_{k=1}^n w_k} \cdot d(ZD(a_{ik}), ZD(a_{jk}))}, & ZD(a_{ik}) \succ ZD(a_{jk}) \\ 0, & ZD(a_{ik}) \sim ZD(a_{jk}) \\ -\frac{1}{\theta} \sqrt{\frac{w_k}{\sum_{k=1}^n w_k} \cdot d(ZD(a_{ik}), ZD(a_{jk}))}, & ZD(a_{ik}) \prec ZD(a_{jk}) \end{cases}. \quad (14)$$

The parameter θ represents the loss aversion coefficient and is set to 1 in this study. The distance between two Z-numbers is calculated as (Zhu, 2022):

$$d(ZD(a_{ik}), ZD(a_{jk})) = \sqrt{\frac{1}{3} [(a_{ik}^l - a_{jk}^l)^2 + (a_{ik}^m - a_{jk}^m)^2 + (a_{ik}^u - a_{jk}^u)^2]}. \quad (15)$$

Step 4. Calculate the overall advantage value of alternative solutions

The overall advantage value A_i of the alternative solutions can be obtained by:

$$S_i = \frac{\sum_j \varsigma(A_i - A_j) - \min_i \sum_j \varsigma(A_i - A_j)}{\max_i \sum_j \varsigma(A_i - A_j) - \min_i \sum_j \varsigma(A_i - A_j)}. \quad (16)$$

Step 5. Prioritize alternative solutions based on their overall advantage value

Priorities are based on the overall advantage values of the alternatives, with higher overall advantage values indicating better solutions.

4. Empirical analysis

An empirical analysis is conducted using data from four Taiwanese airlines, labeled A_1 , A_2 , A_3 , and A_4 , to explore the resilience of each airline using a combined multi-criteria decision-making method.

4.1. Proposed preliminary resilience criteria for the airline industry

The airline industry is a high-value industry in terms of capital, technology, experience, and labor-intensive requirements. Due to its significant industrial linkage effect and high added value, decision-makers in many countries are actively promoting sustainable development and corporate resilience in the airline industry. It is believed that the development of the airline industry can not only drive economic growth but also promote communication and cultural exchange among people. This study illustrates the effectiveness of our methodology through an empirical analysis of four Taiwanese airlines, referred to herein as A_1 , A_2 , A_3 , and A_4 . The first of these, A_1 , headquartered in Taoyuan City, offers both international and domestic flights, with routes covering Asia, Europe, Australia, and the Americas. Its fleet includes Airbus A330, A350, and Boeing 777 aircraft, and the company employs over 14,000 staff, including pilots, flight attendants, and ground crew. A_2 primarily focuses on international routes, offering passenger and cargo services to destinations in over 30 countries, with approximately 250 flights daily. It has a workforce of more than 10,461 employees. A_3 provides mainly medium- and short-haul international flights, with its hub located at Taoyuan International Airport. It services Japan, Northeast Asia, Southeast Asia, and mainland China. Finally, A_4 serves destinations in 21 countries. It has more than 5,000 employees, including pilots, flight attendants, and ground staff.

Based on the background theories and six resilience aspects summarized in Section 2, a further literature review was conducted, along with the collection of opinions from experts with relevant backgrounds in the airline industry. Based on this, we compiled 14 criteria for assessing the resilience of airline enterprises across various indicators. Detailed definitions of these criteria are presented in Table 4.

4.2. Resilience index screening

This study used the modified Delphi method to screen the 14 previously compiled resilience evaluation criteria for the aviation industry. The survey was conducted based on the experts' own experiences, who rated items on a five-point Likert scale and provided feedback. In this case study, 7 expert questionnaires were distributed to individuals in the airline industry who hold relevant positions, including 5 senior airline executives, 1 scholar, and 1 senior airport manager. They all have more than 20 years of relevant experience and hold undergraduate or master's degrees from a university.

The standard deviation and interquartile range of the expert panel's responses were calculated to obtain the reference thresholds. The criteria had to meet the following thresholds: achieving a score in the top quartile (Q3 or above); a standard deviation below 1; and an interquartile range below 0.6. These criteria were considered the most critical evaluation benchmarks. The results showed that out of the 14 original resilience evaluation criteria for airlines, eight met the thresholds, with a high level of consensus among the expert panel.

Table 4. Proposed airline resilience criteria and their definitions

Dimension	Criterion	Definition	References
D_1 Sustainability	Improve aircraft fuel performance and promote green technology	Reducing fuel consumption and emissions through advanced technologies to minimize environmental impact	Albuquerque et al. (2020); Ding et al. (2021)
	Establishment and update of the internal management system in the company	Establishing and updating internal management systems to ensure efficient airline operations	Jiang et al. (2023)
D_2 Robustness	Management thinks positively and does not transfer pressure downwards. Positive leadership without pressure	Leaders motivate employees through supportive and constructive management rather than coercion	Sobieralski (2020)
	Company management and adjustment of the number of flights	Modifying flight schedules in response to market demand, operational requirements, and competitive pressures	Serfontein and Govender (2021); Zhang et al. (2020)
	Adjustment of airfare	Adjusting ticket prices based on demand, competition, and operating costs	Belhadi et al. (2021)
D_3 Flexibility	Switch to passenger cargo mode	Converting passenger aircraft to support cargo transportation when necessary	Tekic and Koroteev (2019)
	Adoption of electronic tickets and online self-service check-in practices	Providing digital ticketing and online services to improve operational flexibility	Tekic and Koroteev (2019)
D_4 Situational Awareness	Sensitivity of management to environmental changes, and being able to enhance abilities beyond their own business	Leaders' ability to perceive environmental changes and act beyond functional boundaries	Serfontein and Govender (2021); Migdadi (2022)
	Flexible scheduling of workforce with partial salary	Adjusting employees' working time, location, and compensation based on operational needs	Migdadi (2022)
D_5 Corporate Strategy	Ways to attract new customers, facilitate the return of existing customers, and transform the experience to provide better responses	Retaining and attracting customers through incentives and improved service quality	Demers et al. (2021); Migdadi (2022)
	Utilizing big data for human resource scheduling	Using big data analytics to optimize workforce planning and scheduling	Demers et al. (2021); Migdadi (2022)
	Activities to provide flight service experience camps at the end of the epidemic	Adjusting services and operations to maintain service quality during pandemics	Demers et al. (2021); Migdadi (2022)
D_6 Financial Capability	Financial soundness and constantly adjusting foreign exchange levels	Maintaining financial stability and managing capital and foreign exchange risks effectively	Jiang et al. (2023); Ding et al. (2021)
	Cash flow lending allows enterprises to make adjustments to changing needs at any time	Securing liquidity through borrowing to support operational continuity	Jiang et al. (2023)

According to the results, the following six criteria were of lesser importance: "establishment and update of internal management system of the company", "adjustment of airline ticket prices by the company", "adoption of electronic tickets and online self-service check-in", "flexible scheduling of local salary for manpower", "activities of providing flight service experience camps at the end of the epidemic", and "borrowing cash flow for enterprises to adjust at any time", so they were deleted. Establishing and updating the internal management system, as well as adopting electronic tickets and online self-service check-in practices, fall under the category of baseline operational practices. In the context of a developed and tightly regulated aviation market like Taiwan, these practices are considered minimum requirements for normal operation, rather than crisis response capabilities. Meanwhile, adjustments to airfare and activities are being made to provide flight service experience camps at the end of the epidemic, which are short-term tactical measures. These measures primarily impact revenue and brand image during the recovery phase, rather than directly enhancing the ability to absorb and maintain core operations during severe disruptions. Cash flow lending, allowing enterprises to adjust to changing needs at any time, and flexible workforce scheduling with partial salaries, fall under the category of externally dependent practices. In the context of Taiwan, these measures are subject to strong institutional regulation and do not fully reflect the intrinsic capacity of enterprises to self-adjust operations in the face of disruption.

In contrast to the excluded criteria, the retained eight criteria do not fall into the categories of baseline operational practices, short-term demand stimulation measures, or institutionally constrained actions. Instead, they represent endogenous operational and strategic capabilities that directly influence airlines' ability to absorb disruptions, adapt operational configurations, and sustain core functions under crisis conditions. Therefore, these criteria exhibit stronger contextual relevance and discriminatory power in assessing operational resilience within the Taiwanese airline industry. Finally, the remaining criteria were categorized into six resilience aspects to construct a hierarchical model for evaluating the resilience of enterprises in the aviation industry. The framework is shown in Figure 2.

4.3. Determine the weights of the criteria

This study employs the Best-Worst Method (BWM) based on rough Z-numbers to determine the weights of resilience indicators/criteria for airline enterprises. The steps in the implementation are as follows:

Step 1. Determine the set of evaluation criteria for the decision-making system

Based on the eight key evaluation criteria selected through the aforementioned Delphi method, a complete hierarchical structure of resilience criteria for enterprises in the airline industry was constructed, as shown in Figure 2.

Step 2. Choose the best criterion (B) and the worst criterion (W)

A questionnaire asked experts to rank the best and worst criteria based on their experience. Different specialists may have varying experiences and opinions on the relevance of the criteria. Results indicate seven experts' top criteria: $B^1 = C_5$, $B^2 = C_5$, $B^3 = C_2$, $B^4 = C_3$, $B^5 = C_5$, $B^6 = C_5$, and $B^7 = C_5$. The worst criteria are: $W^1 = C_4$, $W^2 = C_6$, $W^3 = C_4$, $W^4 = C_7$, $W^5 = C_7$, $W^6 = C_4$, and $W^7 = C_4$.

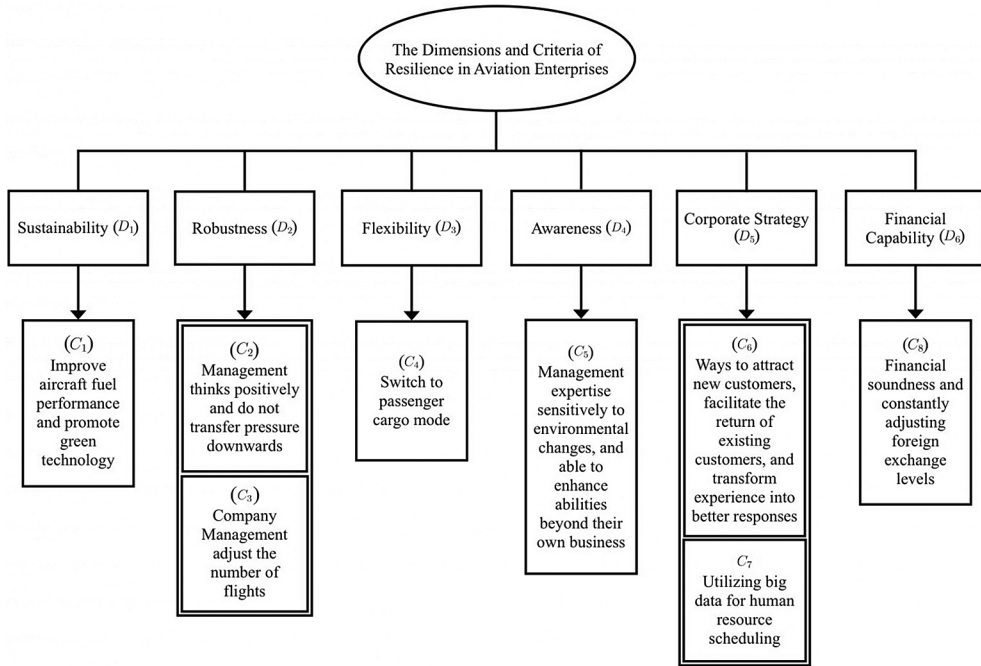


Figure 2. Hierarchical structure of the resilience dimensions and criteria for aviation enterprises

Step 3. Generate the best to others (BO) vector

In this step, the seven experts were asked to complete the survey using the importance and reliability levels provided in Tables 1 and 2. The results represent the relative importance ratios of the best criterion compared to the remaining criteria. Taking Expert 1 as an example, Expert 1 rated the best criterion “experienced leadership, sensitivity to environmental changes, and improvement of abilities beyond their own business (C_5)” as about six times more important than the criterion “improving aircraft fuel performance and promoting green technology (C_1)”, so the answer is given as VI. Based on the reliability evaluation scale in Table 2, Expert 1 considered the reliability level for the above comparison to be high (H), so their answer is H (Table 5).

Table 5. BO vector using linguistic variables

Expert	Best criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
1	C_5	(VI, H)	(VI, H)	(FI, H)	(FI, H)	–	(VI, H)	(VI, H)	(VI, H)
2	C_5	(WI, M)	(VI, M)	(VI, H)	(WI, M)	–	(AI, H)	(VI, H)	(AI, M)
3	C_2	(VI, H)	–	(AI, H)	(FI, VH)	(AI, VH)	(VI, H)	(VI, M)	(AI, H)
4	C_3	(WI, VH)	(VI, M)	–	(EI, M)	(AI, H)	(EI, M)	(EI, M)	(VI, H)
5	C_5	(AI, H)	(FI, M)	(FI, H)	(FI, H)	–	(VI, M)	(AI, H)	(AI, M)
6	C_5	(AI, H)	(VI, H)	(VI, M)	(FI, H)	–	(VI, H)	(AI, H)	(VI, M)
7	C_5	(AI, H)	(VI, H)	(VI, M)	(FI, H)	–	(VI, VH)	(VI, H)	(VI, M)

The preference results of each expert for the best criterion relative to all other criteria are shown in Table 5. Based on Table 1 and Table 2, Expert 1's response (VI, H) is used to explain how the linguistic variables are transformed into fuzzy numbers, where VI is converted to (5, 7, 9) and H is converted to (0.5, 0.7, 0.9). The centroid method (Kang et al., 2012) is applied to obtain the explicit value of the reliability. α , which in this case is equal to 0.5, and then, using Eq. (A2) (Appendix), the V_{BO} triangular fuzzy number matrix can be obtained; see Table A1 (Appendix).

Step 4. Generate the others to worst (OW) vector

Similarly, using the remaining criteria as the benchmark, pairwise comparisons are made with the worst criteria to generate the OW (Others to the worst) vectors, which are then converted into triangular fuzzy number form, as shown in Table A2 (Appendix).

Step 5. Convert the BO and OW into rough set Z-numbers

Applying Eqs. (A3)–(A6) (Appendix), matrices V_{BO} and V_{OW} can be transformed into the rough Z vectors, $RZ(V_{BO})$ and $RZ(V_{OW})$. Taking the lower bound interval of C_1 as an example, $(4.18 + 0.70 + 4.18 + 0.93)/4 = 2.50$, $(4.18 + 4.18 + 5.85 + 5.85 + 5.85)/5 = 5.19$. The results of $RZ(V_{BO})$ and $RZ(V_{OW})$ are shown in Table A3 and Table A4 (Appendix).

Then, using the Dombi method (Eqs. (4)–(5)), we can aggregate the opinions of seven experts on the rough Z-number vectors (Tables A3 and A4 in the Appendix). The integrated BO and OW vectors can be obtained as shown in Table 6.

Step 6. Calculate the optimal weights of the criteria

Utilizing the BWM algorithm proposed by Rezaei (2015), the optimal criterion weights for the experts can be solved for according to Eqs. (6), and transformed into crisp values using Eq. (9), as shown in Table 6. Among the eight criteria for resilience evaluation of aviation enterprises, "experienced leadership, sensitivity to environmental changes, and improvement of abilities beyond their own business (W_5)" is the most important criterion.

Table 6. Aggregated BO and OW vectors in rough Z numbers and criteria weight values

	$RZ(V_{BO})$	$RZ(V_{OW})$	Fuzzy weight	Weight	Rank
C_1	[1.49, 4.58], [3.34, 6.35], [4.72, 6.86]	[1.54, 4.13], [3.32, 5.74], [5.00, 7.21]	0.11, 0.12, 0.14	0.1326	2
C_2	[2.98, 4.77], [4.47, 6.41], [5.87, 7.15]	[2.73, 4.16], [4.30, 5.93], [5.87, 7.69]	0.11, 0.12, 0.13	0.1058	5
C_3	[3.10, 4.78], [4.74, 6.37], [6.16, 6.99]	[2.76, 3.86], [4.38, 5.56], [6.00, 7.25]	0.10, 0.10, 0.11	0.0972	6
C_4	[1.36, 2.46], [1.95, 4.08], [3.82, 5.84]	[1, 1], [1, 1], [1, 1]	0.03, 0.04, 0.06	0.0504	8
C_5	[1, 1], [1, 1], [1, 1]	[4.44, 5.61], [6.15, 7.41], [7.64, 8.07]	0.28, 0.30, 0.33	0.3071	1
C_6	[1.98, 4.91], [2.34, 6.57], [4.28, 7.70]	[1.72, 3.95], [2.22, 5.68], [4.27, 7.47]	0.08, 0.08, 0.13	0.1192	4
C_7	[2.03, 4.91], [2.41, 6.56], [4.32, 7.60]	[1.59, 3.38], [2.09, 5.03], [4.00, 6.74]	0.05, 0.06, 0.08	0.0626	7
C_8	[4.10, 5.67], [5.66, 6.96], [6.65, 7.69]	[3.77, 4.85], [5.27, 6.54], [6.65, 7.69]	0.11, 0.12, 0.14	0.1249	3

4.4. Airline resilience analysis

After applying the rough Z BWM method to obtain the weights of the criteria, we evaluated to explore the resilience of four major Taiwanese airlines. The Z-number TODIM method was used to calculate the utility of each alternative solution. The results serve as a guide for performance improvement among the four airlines. The detailed steps for the TODIM calculation are as follows:

Step 1. Collect expert evaluation opinions through linguistic variables

Experts' evaluation opinions were collected through linguistic variables (Table 7), followed by the conversion of the semantic tables into Z numbers using Table 2 and Table 3. For example, Expert 1's response was medium good and very high confidence (MD, VH) under the C1 criterion of A1 Airlines, which was explained, with MD being (0.7, 0.9, 1.0) and VH being (0.7, 0.9, 1.0).

Table 7. Performance matrix of expert 1

	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈
A ₁	(MD/VH)	(MD/VH)	(MD/VH)	(G, VH)	(MD, VH)	(MD, VH)	(G, VH)	(MD/VH)
A ₂	(VG/H)	(MD/H)	(VG, H)	(VG, H)	(MD, H)	(VG, H)	(MD, H)	(VG/H)
A ₃	(P/H)	(G/H)	(F, H)	(P, H)	(G, H)	(F, VH)	(F, H)	(P/H)
A ₄	(G/H)	(G/H)	(G, H)	(P, H)	(G, H)	(MD, H)	(F, H)	(G/H)

Step 2. Convert the Z numbers into triangular fuzzy numbers

Then convert it into fuzzy number form according to Eqs. (A1)–(A2) (Table A5 in Appendix), and use Eq. (11) to integrate the performance matrices of all experts as shown in Table 8.

Table 8. Performance matrix after integrating expert opinions

	A ₁	A ₂	A ₃	A ₄
C ₁	(0.52, 0.70, 0.83)	(0.64, 0.78, 0.83)	(0.07, 0.22, 0.37)	(0.38, 0.54, 0.70)
C ₂	(0.50, 0.66, 0.84)	(0.61, 0.76, 0.84)	(0.19, 0.33, 0.52)	(0.39, 0.53, 0.69)
C ₃	(0.53, 0.71, 0.85)	(0.61, 0.77, 0.84)	(0.14, 0.32, 0.48)	(0.37, 0.53, 0.68)
C ₄	(0.48, 0.66, 0.82)	(0.65, 0.78, 0.84)	(0.10, 0.27, 0.42)	(0.24, 0.44, 0.61)
C ₅	(0.65, 0.83, 0.93)	(0.58, 0.75, 0.83)	(0.41, 0.58, 0.75)	(0.41, 0.58, 0.75)
C ₆	(0.59, 0.75, 0.85)	(0.56, 0.73, 0.85)	(0.15, 0.32, 0.48)	(0.39, 0.57, 0.70)
C ₇	(0.59, 0.79, 0.88)	(0.57, 0.77, 0.85)	(0.14, 0.37, 0.41)	(0.34, 0.50, 0.61)
C ₈	(0.61, 0.78, 0.87)	(0.61, 0.74, 0.78)	(0.13, 0.31, 0.47)	(0.44, 0.59, 0.71)

Step 3. Calculate the relative advantages of the airlines

Applying Eqs. (14)–(15), First, we calculate the relative advantage of the dominant position A_i over the alternative solution A_j under each criterion. The calculation results are shown in Table 9. Taking criterion C₁ as an example, calculate the relation of airline A₁ to A₂ as follows:

$$-\left(\left(0.333 * \left((0.52 - 0.64)^2 + (0.70 - 0.77)^2 + (0.83 - 0.82)^2\right)^{0.5}\right)\right) = -0.083.$$

Table 9. Relative advantage matrix of the airlines

C_1	A_1	A_2	A_3	A_4
A_1	–	0.083	–0.463	–0.143
A_2	–0.083	–	–0.530	–0.215
A_3	0.463	0.530	–	0.320
A_4	0.143	0.215	–0.320	–
...	...	...	...	...
C_8	A_1	A_2	A_3	A_4
A_1	–	–0.059	–0.449	–0.175
A_2	0.059	–	–0.411	–0.138
A_3	0.449	0.411	–	0.275
A_4	0.175	0.138	–0.275	–

Continuing with the previously calculated weight values, the overall result of the dominant position A_i of the alternative solution over the other alternative solution A_j can be calculated. The calculation results are shown in Table 10. Taking A_1 to A_2 as an example,

$$-\left((0.13 * (-0.083)) + (0.10 * (-0.07)) + (0.09 * (-0.05)) + (0.05 * (-0.11)) + (0.30 * 0.01) + (0.11 * (-0.11)) + (0.06 * 0.02) + (0.12 * 0.059)\right)^{0.5} = -0.140,$$

where 0.13, 0.10, 0.09...0.12 are the criteria weights obtained from the modified BWM method.

Table 10. Overall advantage matrix of airlines and Overall advantage values (S_i)

	A_1	A_2	A_3	A_4	S_i	Rank
A_1	–	0.140	–0.632	–0.420	0.732	2
A_2	–0.140	–	–0.647	–0.443	0.782	1
A_3	0.632	0.647	–	0.473	0.276	4
A_4	0.420	0.443	–0.473	–	0.512	3

Step 4. Calculate the overall advantage for each airline

Equation (16) can be used to calculate the S_i values, which are prioritized based on their overall advantage value. The higher the overall advantage value, the better the alternative solution. The final ranking results are shown in Table 10.

According to Table 10, the four leading alternative solutions can be prioritized as follows $A_2 \succ A_1 \succ A_4 \succ A_3$. The results indicate that among the four major airlines, A2 exhibits the best resilience performance among the evaluated airline enterprises. Furthermore, using the Z-number TODIM method calculation results as the benchmark, the S_i value of A_2 has the highest value among all alternatives.

5. Discussion and management implications

The importance of the airline industry as an international mode of transportation in Taiwan makes the resilience of airline enterprises particularly crucial. To strengthen this resilience, this study proposes a hybrid evaluation model. The model employs the rough set Z-number BWM method to determine optimal criterion weights and the Z-number TODIM method to calculate the gap between each alternative solution and the desired level, thereby ranking the alternatives. Based on the research results, this study proposes the following management implications.

In the context of rapid development and fierce competition in modern times, airlines should establish cooperative relationships with external experts and institutions and regularly hold seminars and training courses to improve leaders' sensitivity to environmental changes. They should also establish cross-departmental cooperation mechanisms to break down departmental silos, actively leverage organizational performance, and enhance operational efficiency. Additionally, strengthening team collaboration and communication will enhance leaders' ability to adapt in diverse environments. These results echo the findings of Sabillon et al. (2023).

Furthermore, the experts believe that "improving aircraft fuel performance and promoting green technology (W_1)" is the second most influential evaluation criterion under the sustainability dimension. This study suggests that advanced flight management systems and avionics technology should be adopted, which, in accordance with the United Nations Sustainable Development Goals (SDGs) and ESG, would reduce air wait times and unnecessary fuel consumption. Companies can implement improvements through technological innovation, flight operation optimization, and enhanced environmental awareness to achieve improved aircraft fuel performance and promote green technology (Ding et al., 2021). They should also formulate policies for sustainable supply chain development by incorporating international norms for sustainability, including environmental, human rights, labor practices, and social impact, into the reference criteria for selecting new supplier partners. It is expected that the company's procurement policies and practices will be integrated with sustainability regulations to ensure responsible sourcing.

"Financial Soundness and Real-Time Adjustment of Foreign Exchange Levels (W_8)" ranks as the third most influential evaluation criterion under the dimension of financial capability. Enhancing financial soundness through diversification of revenue sources and effective cost management can reduce reliance on a single market or product. Additionally, establishing strong relationships with banks and financial institutions is crucial to ensuring the ability to adjust foreign exchange levels promptly when needed, mitigating the adverse effects of foreign exchange risks (Jiang et al., 2023). Although the above recommendations are based on data from Taiwanese airlines in the case study, they apply to airlines worldwide. These three primary evaluation criteria can serve as priorities for improvement to enhance resilience.

According to the results of the Z-number TODIM method described above, the performance of A_2 can serve as a benchmark for A_1 , A_3 , and A_4 . Airline A_2 has developed a sound and comprehensive training system and framework for cultivating professional talent in the areas of "experienced leadership, sensitivity to environmental changes, and improvement of

abilities beyond their own business (C_5)” by combining diverse learning methods in real-world and e-learning courses, and investing heavily in hardware and software for training. This airline attaches great importance to the development of employee capabilities and ensures the integration of practical training and application. For example, A_2 has a “Talent Cultivation Committee” that regularly reviews and improves matters related to the cultivation of potential talents in the company. Candidates are selected for training and development through recommendations from various units and approved by the committee. During the training period, work rotations are arranged promptly to expand the individual’s experience, and business management courses are provided to enhance their knowledge and skills, thereby cultivating management talents with the necessary abilities and experience. During the period of COVID-19, this included “training related to increasing cargo revenue”. Efforts were made to strengthen the professional knowledge of the cargo loading personnel for the new 777 cargo plane. The number of flight crew members capable of working with the 777 cargo plane was increased. In addition, with the gradual resumption of normal operations in response to the easing of the pandemic, “enhanced passenger service training” became crucial for improving cabin crew service functions.

In terms of “improving aircraft fuel performance and promoting green technology (C_1)”, airlines can improve fleet efficiency by introducing new aircraft models and services, while phasing out old aircraft with higher energy consumption. This would help to reduce greenhouse gas emissions. Airlines should also establish research centers focused on green technology, collaborate with environmental protection agencies, master international carbon control mechanisms, reduce cabin waste, and address sustainable aviation fuel issues. They should participate actively in government policy-making and continuously promote industry training initiatives. Participation in the International Air Transport Association (IATA) CO₂ Connect flight carbon footprint calculator testing program would also enable planners to identify new trends for improving and developing international carbon footprint calculation tools. To assist in meeting the net-zero emissions target by 2050, airlines should strive to incorporate Sustainable Aviation Fuel (SAF) into their net-zero carbon emissions path planning and consider relevant supporting measures and alternative mechanisms. In addition to their own operations, airlines should consider various factors in supplier selection, such as quality, delivery time, priority procurement of local raw materials, and the supplier’s own sustainable (ESG) performance, in order to create positive feedback in the overall value chain, as well as promote green consumption, implement green and local procurement, and sustainable procurement practices.

Finally, in terms of improving “financial soundness and constantly adjusting foreign exchange levels (W_8)”, airlines can focus on diversification of revenue sources and cost management. The post-pandemic era remains characterized by numerous uncertainties. Faced with a tumultuous business environment, rapidly changing market challenges, and rising aviation fuel prices, airline management must maintain a cautious attitude, adapt flexibly to the times, dynamically adjust passenger and cargo sales plans, respond to market changes, leverage cargo operation advantages, and comprehensively grasp niche markets. Enterprises must continually promote sustainable practices, actively implement various risk management strategies, establish corresponding response plans, and adjust their management systems

flexibly in accordance with international standards of corporate governance and market trends. Although A_2 's overall performance is relatively good compared to other Taiwanese airlines, there is still a clear gap between all airlines and the desired aspiration level. Airline industry managers must understand the room for improvement their respective airlines still have and encourage them to continue making improvements to achieve the desired goals.

To ensure the robustness of the results, a sensitivity analysis was conducted. The weight of the most influential criterion (C_5) was changed from 0.1 to 0.9, while the weights of the other criteria were proportionally altered based on their respective ratios. This vast range of variance was intended to depict extreme decision-making preferences. As demonstrated in Table 11, the ranking order of the four airlines remained constant across all situations, indicating that the evaluation results are robust and unaffected by significant variations in criterion priority.

Furthermore, a comparative analysis with other models was conducted, yielding consistent outcomes (see Table 12). Although different MCDM ranking approaches provide the same ranking orders, this should not be regarded as duplication in the suggested framework. Instead, the consistency of rankings is due to the stabilizing impact of combining imprecise Z-numbers with Dombi aggregation, which clearly captures both uncertainty and reliability in expert ratings. By enhancing the quality and coherence of the aggregated input information, the proposed framework ensures that different ranking approaches yield more informed and credible decisions, leading to reliable and consistent results.

Table 11. Results of sensitivity analysis

	Original weight	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9
A_1	2	2	2	2	2	2	2	2	2	2
A_2	1	1	1	1	1	1	1	1	1	1
A_3	4	4	4	4	4	4	4	4	4	4
A_4	3	3	3	3	3	3	3	3	3	3

Table 12. Model comparisons

	SAW	TOPSIS	VIKOR	WASPAS	PROMETHEE	Proposed TODIM
A_1	2	2	2	2	2	2
A_2	1	1	1	1	1	1
A_3	4	4	4	4	4	4
A_4	3	3	3	3	3	3

Sensitivity investigation and model comparison results reveal that airline rankings do not change when key criteria weights are modified over a wide range, or when various MCDM ranking algorithms are used. This phenomenon should not be viewed as redundancy in the suggested model, but rather as a reflection of the evaluation process's exceptional stability and consistency. In fact, the integrated methodology's main contribution lies in the input data gathering and processing stage, rather than the final ranking mechanism. Combining rough Z-numbers with the Dombi operator enables the simultaneous modeling of uncertainty and

reliability in expert evaluations, thereby reducing noise, inconsistencies, and extreme ratings in the input data. When input information is aggregated in a more consistent and trustworthy manner, different ranking systems produce similar results, increasing the dependability of the findings. As a result, the consistency of rankings among MCDM methods, as well as the stability of sensitivity analysis, can be interpreted as indirect evidence of the proposed methodology framework's effectiveness in improving the quality and reliability of operational resilience assessments, rather than simply creating ranking differences.

6. Conclusions and suggestions for future work

There has been no prior research specifically addressing airline resilience and its evaluation. This study proposes a hybrid multi-criteria decision-making model to explore airline resilience. The model overcomes some of the limitations of traditional methods by first constructing an evaluation framework through a literature review and expert survey responses. The proposed model is then used to understand the relative importance of the resilience criteria, followed by a case study analysis of four Taiwanese airlines to demonstrate the model's practicality and effectiveness. The contributions are summarized below.

- (1) This study uses Delphi and Dombi aggregating methods to choose criteria. The 14 literature review criteria were reduced to eight through expert surveys, creating a new hierarchical model for business resilience.
- (2) The approximation set Z-number BWM approach successfully determines criterion weights in decision-making with many experts. An updated BWM method utilizes the rough Z-number technique to convert language variables into numerical responses, thereby reducing expert uncertainty and inconsistency. Thus, the resulting weights should be more accurate than those obtained from the original BWM approach. The results show that "experienced leaders, sensitive to environmental changes, and improving abilities beyond their own business (C_5)", "improving aircraft fuel performance and promoting green technology (C_1)", and "financial soundness and foreign exchange adjustment level at any time (C_8)" are the most important evaluation criteria.
- (3) The Z-TODIM can improve the performance evaluation of Taiwan Airlines by identifying which airlines excel in each criterion. Aspiration levels are added, and the distance between alternate solutions and them is established to better reflect the actual scenario. Results reveal A_2 is the most resilient airline.
- (4) Utilizing Dombi instead of average values helps improve data integration and reduce outliers.

The hybrid MCDM framework developed in this study was applied to evaluate airline operational resilience, providing an analytical foundation for airlines to assess their current performance and formulate evidence-based strategic decisions. Several directions for future research are suggested. Future studies could integrate fuzzy set theory and grey relational analysis to more effectively address the uncertainty inherent in expert judgments, particularly when dealing with discrete data and imprecise information. Additionally, when inter-relationships exist among evaluation criteria, techniques such as DEMATEL and DANP could be employed to construct influential network diagrams and derive weights that account for such dependencies. The proposed six-dimensional resilience framework—encompassing

sustainability, robustness, adaptability, awareness, corporate strategy, and financial capabilities—could be extended to other critical sectors including defense, automotive manufacturing, and related industries. Furthermore, while this study examines four airlines operating within Taiwan's aviation market under uniform regulatory conditions, future investigations could apply the framework to airlines in different geographical regions, alternative business models, or varied operational environments to validate its broader applicability and generalizability.

Funding

This research was supported by National Science and Technology Council (Taiwan) project number 113-2625-M-027-008.

Author contributions

J.J.H.L.: Conceptualization, correction and supervision. HL Liu: Writing manuscript, analysis, methodology. C.Y. Hu: Data collection and calculation. Y.C. Chuang: Calculation check and analysis confirmation. All the authors have read and agreed to the published version of the manuscript.

Conflict of interest

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

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APPENDIX

Rough Z numbers

The approximation set Z-numbers include language variable Z-numbers formed during evaluation. Evaluation findings are split into A and B in the Z-number method for expert opinions. Part A represents the expert's score for the evaluation object, whereas Part B represents the expert's reliability assessment. Language Z-numbers are used by specialists to indicate their judgments during evaluation. Then, triangular fuzzy numbers quantify the linguistic Z-numbers to capture expert evaluation fuzziness. The centroid approach can be used to transform Part B of the Z number (reliability) into a clear value:

$$\alpha = \frac{\int \chi \mu_B(\chi) d\chi}{\int \mu_B(\chi) d\chi}. \quad (A1)$$

After obtaining an explicit value for the reliability of B, the Z number can be converted into a traditional triangular fuzzy number through

$$Z' = (\sqrt{\alpha}a_1, \sqrt{\alpha}a_2, \sqrt{\alpha}a_3). \quad (A2)$$

For a definition of Z-numbers, the interested reader can refer to Kang et al. (2012). The methodology for combining the Rough with the Z-number to form the approximate Z-number is introduced below.

Let U be the set of universes containing all regular fuzzy numbers evolved from the original Z number.

Thus, $\Theta = \{Z_1, Z_2, \dots, Z_n\}$ is a fuzzy number class that covers all objects in U and $Z_1 < Z_2 < \dots < Z_n$; Y is any object of U .

The lower approximation of Z_i is defined as follows:

$$\begin{aligned} \underline{Apr}(z_i^l) &= \cup \{Y \in U \mid \Theta^l(Y) \leq z_i^l\}, \\ \underline{Apr}(z_i^m) &= \cup \{Y \in U \mid \Theta^m(Y) \leq z_i^m\}, \\ \underline{Apr}(z_i^u) &= \cup \{Y \in U \mid \Theta^u(Y) \leq z_i^u\} \end{aligned} \quad (A3)$$

The upper approximation of Z_i is defined as:

$$\begin{aligned} \overline{Apr}(z_i^l) &= \cup \{Y \in U \mid \Theta^l(Y) \geq z_i^l\}, \\ \overline{Apr}(z_i^m) &= \cup \{Y \in U \mid \Theta^m(Y) \geq z_i^m\}, \\ \overline{Apr}(z_i^u) &= \cup \{Y \in U \mid \Theta^u(Y) \geq z_i^u\} \end{aligned} \quad (A4)$$

The lower limitation of Z_i is defined as:

$$\begin{aligned} \underline{\lim}(z_i^l) &= \frac{1}{N_L^l} \sum_{i=1}^{N_L^l} Y \in \underline{Apr}(z_i^l), \\ \underline{\lim}(z_i^m) &= \frac{1}{N_L^m} \sum_{i=1}^{N_L^m} Y \in \underline{Apr}(z_i^m), \\ \underline{\lim}(z_i^u) &= \frac{1}{N_L^u} \sum_{i=1}^{N_L^u} Y \in \underline{Apr}(z_i^u) \end{aligned} \quad (A5)$$

The upper limitation of Z_i is defined as:

$$\begin{aligned}\overline{\lim}(z_i^l) &= \frac{1}{N_U^l} \sum_{i=1}^{N_U^l} Y \in \overline{\text{Apr}}(z_i^l), \\ \overline{\lim}(z_i^m) &= \frac{1}{N_U^m} \sum_{i=1}^{N_U^m} Y \in \overline{\text{Apr}}(z_i^m), \\ \overline{\lim}(z_i^u) &= \frac{1}{N_U^u} \sum_{i=1}^{N_U^u} Y \in \overline{\text{Apr}}(z_i^u)\end{aligned}\quad (\text{A6})$$

In the above equations l , m , and u represent the lower, middle, and upper bounds, respectively; N_U^l , N_U^m , and N_U^u are the quantities contained in the corresponding element of $\overline{\text{Apr}}(z_i^l)$, $\overline{\text{Apr}}(z_i^m)$ and $\overline{\text{Apr}}(z_i^u)$. Similarly, N_U^l , N_U^m and N_U^u are the quantities contained in the corresponding elements of $\overline{\text{Apr}}(z_i^l)$, $\overline{\text{Apr}}(z_i^m)$ and $\overline{\text{Apr}}(z_i^u)$.

Thus, the Z number of the approximate set is defined as follows:

$$\begin{aligned}RZ(Z_i) &= ([z_i^{lL}, z_i^{lU}], [z_i^{mL}, z_i^{mU}], [z_i^{uL}, z_i^{uU}]) = \\ &([\underline{\lim}(z_i^l), \overline{\lim}(z_i^l)], [\underline{\lim}(z_i^m), \overline{\lim}(z_i^m)], [\underline{\lim}(z_i^u), \overline{\lim}(z_i^u)]).\end{aligned}\quad (\text{A7})$$

From the above definition, the three rough set intervals in the triangular fuzzy number Z_i can be obtained.

Table A1. BO vector in fuzzy form

Expert	Best	C_1	C_2	...	C_8
1	C_5	(4.18, 5.85, 7.52)	(4.18, 5.85, 7.52)	...	(3.53, 4.94, 6.36)
2	C_5	(0.70, 2.12, 3.53)	(3.53, 4.94, 6.36)	...	(4.94, 6.36, 6.36)
3	C_2	(4.18, 5.85, 7.52)	(0.83, 0.83, 0.83)	...	(5.85, 7.52, 7.52)
4	C_3	(0.93, 2.79, 4.65)	(3.53, 4.94, 6.36)	...	(3.53, 4.94, 6.36)
5	C_5	(5.85, 7.52, 7.52)	(2.12, 3.53, 4.94)	...	(6.51, 8.37, 8.37)
6	C_5	(5.85, 7.52, 7.52)	(4.18, 5.85, 7.52)	...	(4.18, 5.85, 7.52)
7	C_5	(5.85, 7.52, 7.52)	(4.18, 5.85, 7.52)	...	(3.53, 4.94, 6.36)

Table A2. OW vector in fuzzy form

Expert	Worst	C_1	C_2	...	C_8
1	C_4	(4.18, 5.85, 7.52)	(4.18, 5.85, 7.52)	...	(3.53, 4.94, 6.36)
2	C_6	(0.83, 2.50, 4.18)	(4.18, 5.85, 7.52)	...	(3.53, 4.94, 6.36)
3	C_4	(2.12, 3.53, 4.94)	(4.18, 5.85, 7.52)	...	(4.18, 5.85, 7.52)
4	C_7	(0.83, 2.50, 4.18)	(2.12, 3.53, 4.94)	...	(3.53, 4.94, 6.36)
5	C_7	(4.94, 6.36, 6.36)	(4.65, 6.51, 8.37)	...	(4.65, 6.51, 8.37)
6	C_4	(4.65, 6.51, 8.37)	(2.50, 4.18, 5.85)	...	(5.85, 7.52, 7.52)
7	C_4	(4.18, 5.85, 7.52)	(4.18, 5.85, 7.52)	...	(3.53, 4.94, 6.36)

Table A3. BO vector in rough Z numbers

Expert	Best	C_1	...	C_8
1	C_5	([2.50, 5.19], [4.16, 6.86], [6.55, 7.53])	...	([3.53, 5.21], [4.94, 6.21], [6.36, 7.42])
2	C_5	([0.71, 3.94], [2.12, 5.60], [3.53, 6.55])	...	([4.24, 5.77], [6.11, 7.42], [6.36, 7.42])
3	C_2	([2.50, 5.19], [4.16, 6.86], [6.55, 7.53])	...	([4.78, 6.18], [6.58, 7.95], [6.94, 7.95])
4	C_3	([0.82, 4.48], [2.46, 6.18], [4.10, 7.05])	...	([3.53, 5.21], [4.94, 6.21], [6.36, 7.42])
5	C_5	([3.94, 5.86], [5.60, 7.53], [6.55, 7.53])	...	([5.21, 6.51], [7.03, 8.37], [7.42, 8.37])
6	C_5	([3.94, 5.86], [5.60, 7.53], [6.55, 7.53])	...	([4.56, 5.85], [5.85, 7.03], [6.94, 7.95])
7	C_5	([3.94, 5.86], [5.60, 7.53], [6.55, 7.53])	...	([3.53, 5.21], [4.94, 6.21], [6.36, 7.42])

Table A4. OW vector in rough Z numbers

Expert	Worst	C_1	...	C_8
1	C_4	([2.38, 4.59], [3.96, 6.24], [5.75, 7.95])	...	([3.53, 4.55], [4.94, 6.21], [6.36, 7.42])
2	C_6	([0.83, 3.35], [2.51, 4.96], [4.18, 6.28])	...	([3.53, 4.55], [4.94, 6.21], [6.36, 7.42])
3	C_4	([1.47, 3.97], [3.02, 5.57], [4.56, 6.81])	...	([3.85, 4.89], [5.40, 6.63], [6.94, 7.95])
4	C_7	([0.83, 3.35], [2.51, 4.96], [4.18, 6.28])	...	([3.53, 4.55], [4.94, 6.21], [6.36, 7.42])
5	C_7	([3.35, 4.94], [3.97, 6.24], [6.28, 8.38])	...	([4.12, 5.26], [5.77, 7.02], [7.42, 8.37])
6	C_4	([2.38, 4.60], [3.97, 6.25], [6.28, 8.37])	...	([4.55, 5.86], [6.21, 7.52], [6.94, 7.95])
7	C_4	([2.38, 4.59], [3.96, 6.24], [5.75, 7.95])	...	([3.53, 4.55], [4.94, 6.21], [6.36, 7.42])

Table A5. Fuzzy performance matrix of expert 1

	A_1	A_2	A_3	A_4
C_1	(0.65, 0.83, 0.93)	(0.75, 0.83, 0.83)	(0.08, 0.25, 0.41)	(0.41, 0.58, 0.75)
C_2	(0.65, 0.83, 0.93)	(0.58, 0.75, 0.83)	(0.41, 0.58, 0.75)	(0.41, 0.58, 0.75)
C_3	(0.65, 0.83, 0.93)	(0.75, 0.83, 0.83)	(0.25, 0.41, 0.58)	(0.41, 0.58, 0.75)
C_4	(0.46, 0.65, 0.83)	(0.75, 0.83, 0.83)	(0.08, 0.25, 0.41)	(0.08, 0.25, 0.41)
C_5	(0.65, 0.83, 0.93)	(0.58, 0.75, 0.83)	(0.41, 0.58, 0.75)	(0.41, 0.58, 0.75)
C_6	(0.65, 0.83, 0.93)	(0.75, 0.83, 0.83)	(0.25, 0.41, 0.58)	(0.58, 0.75, 0.83)
C_7	(0.46, 0.65, 0.83)	(0.58, 0.75, 0.83)	(0.25, 0.41, 0.58)	(0.25, 0.41, 0.58)
C_8	(0.65, 0.83, 0.93)	(0.75, 0.83, 0.83)	(0.08, 0.25, 0.41)	(0.41, 0.58, 0.75)