

Article

Evaluating the Performance-Shaping Factors of Air Traffic Controllers Using Fuzzy DEMATEL and Fuzzy BWM Approach

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Abstract: In the air traffic management domain, a set of performance-shaping factors are defined to characterize how such factors influence the overall performance of air traffic controllers. While it is worth understanding the nature of these factors, including their priority for policymaking and strategy implementation, no research in the extant literature has conducted an in-depth investigation of this matter. Therefore, this paper aims to explore the performance-shaping factors of air traffic controllers by using fuzzy DEMATEL and fuzzy BWM—such methodologies in the classification of factors as well as their corresponding priority vector. As an illustration, a case study in the Mactan Control Tower of the Civil Aviation Authority of the Philippines (CAAP) is conducted. The key results of the hybrid methodology showed that causal factors are ‘situation awareness,’ ‘communication,’ ‘teamwork,’ ‘vigilance,’ and ‘attention.’ Effect factors are ‘workload,’ ‘trust,’ ‘fatigue,’ and ‘stress.’ Furthermore, ‘communication’ is found to be of the highest priority among other factors. The results can provide relevant insights to the decision-makers of air traffic management in formulating programs and strategies related to the improvement of air traffic controllers’ performance. Note, however, that the study is limited to identifying the inherent characteristics of the factors and their priority ranking; specific plans of action for improving the performance of air traffic controllers are not provided. As a future research direction, the inputs obtained in this paper can pave the way to a more in-depth analysis of improving the performance of air traffic controllers.



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1. Introduction

Different thematic analyses relating to the commercial aviation industry have gained significant attention in the literature since the 1920s because of their undeniable benefits to the general air transportation system and the prominent issues they confront. Such issues revolve around aspects relating to the environment (e.g., carbon emissions, sustainable food waste management) [1–4], health [5–7], economics [8,9], operational efficiency (e.g., on-time performance, routing of flights, ground handling) [10,11], society (e.g., flight booking scheme, passenger satisfaction) [12,13], and safety (e.g., workload, design, fatigue, human performance [14–17]. At a closer look, the most pressing concern that most scholarly works emphasize is general air transportation safety. In fact, the safety of every flight is highly desired by key stakeholders of the commercial aviation industry (i.e., airlines industry, airport management, and air traffic services) from the departure of flights until their arrival, considering that hundreds of lives are at stake should aviation errors result to an unfortunate mishap [18]. The strands under air transportation safety extend to multiple facets of designs specific to aircraft and machine interface, process efficiency, and human performance, to name a few. Among these considerations, humans are highly capitalized in nearly every operation, from strategic planning to its eventual task execution. For instance, pilots maneuver aircraft in all the phases of flight with the aid of air traffic control communication [19,20], while ground handlers are assigned to oversee procedures and

equipment necessary to ensure that the next flight leg is ready and sound [21]. On the other hand, air traffic controllers are involved in surface operations management, which includes giving directions to aircraft among stands, taxiways, holding areas, and runways while ensuring a minimum separation distance between aircraft for safe arrivals and departures [22,23]. Therefore, it is necessary to build on a strong workforce whose overall aptitude for their respective aviation tasks is considered outstanding in order to accomplish such tasks efficiently. These comprise the concept of human performance envelope (HPE) consisting of nine human performance factors, also known as performance-shaping factors, as follows: situation awareness (SA), workload, communication, teamwork, trust, fatigue, stress, vigilance, and attention [24,25].

The HPE concept suggests covering a wide array of factors that can significantly affect human performance and further detect when one or more factors fall short of tolerance [24]. According to the envelope metaphor, looking into a set of interdependent factors is needed to improve human–machine interaction designs in the aviation industry instead of examining only one or two human factors affecting performance. Unfortunately, prior works in the literature focused solely on the characterization of a factor toward another factor. For instance, ref. [26] focused on the multifactor analysis of workload and SA in varying levels of automation. They found that workload and SA are definitely related in ways that even in high workload and good SA or low workload and poor SA, the performance of air traffic controllers remains the same.

On the other hand, ref. [27] confirmed that the level of automation may affect SA, considering that the actual interaction of air traffic controllers (e.g., being a human-outside-the-loop entity) in operational control and monitoring tasks may vary with the level of automation. Moreover, ref. [28] also agreed on the negative influence of automation, particularly on wider applications in remote air traffic control systems, on the SA of air traffic controllers. Taking the relationships between factors in isolation from the general set of factors, such as the case in the previous works, it appears to be rather inadequate due to the exclusivity introduced. When the relationships among factors are examined one at a time (i.e., one factor to another), the inherent interaction among a combination of one or more factors toward another factor is considerably neglected, resulting in weaker generalizations and misinterpretations of the actual inherent relationships among factors given the complex and changing characteristics of air traffic control operations. In other words, since these factors co-exist in the working environment of air traffic controllers, it is only fitting to measure and analyze these together rather than taking each into isolation [29,30]. Furthermore, while previous works can identify the relationship between one factor and another, the corresponding strength of a relationship is not established objectively. Such relationship strength is integral to understanding how factors should be treated with respect to improving performance in the overall sense. Relevant countermeasures can also be significantly framed according to these established relationships. At a closer look, therefore, evaluating the complex relationships among a full range of factors covered in the HPE concept can be better represented as a multicriteria decision-making (MCDM) problem.

The MCDM approach is designed to evaluate the distinct and even conflicting relationships among criteria according to the judgment of subject matter experts [31]. The approach ranges from a variant of criteria assessment tools, that is, decision-making trial an evaluation laboratory (DEMATEL) [32], analytic network process (ANP) [33], interpretive structural modeling (ISM) [34], Matriced' Impacts Croise's Multiplication Appliquée a UN Classement (MICMAC) [35], best-worst method (BWM) [36], to alternative evaluation tools being preference ranking organization method for enrichment evaluations (PROMETHEE) [37–39], analytic hierarchy process (AHP) [40], the technique for order of preference by similarity to ideal solution (TOPSIS) [41], VIKOR (the Serbian name, VIseKriterijumska Optimizacija I Kompromisno Ršenje) [42,43], Elimination Et Choix Traduisant la REalité (ELECTRE) [44], data envelopment analysis (DEA) [45], or a hybrid combination and extensions thereof. In fact, the MCDM approach is successfully applied in various domains which consider the evaluation of interrelationships among factors, such as in the

redesign of warning signs following the ergonomics principles [46], premature closure of microbusiness enterprise [47], sustainable supplier selection in the healthcare sector [48], optimizing crop mix subject to constraints in environment and economic considerations [49], aircraft and helicopter selection [50–52], to name a few.

In the case of the air transport domain, the MCDM approach is widely applied to tackle diverse cases as follows: (a) mitigating airport congestion using fuzzy DEMATEL-ANP and an integrated fuzzy DEMATEL-ANP-TOPSIS, respectively [53,54]; (b) minimizing departure delays using DEMATEL-AHP technique [55]; (c) evaluating the performance of airports based on sustainability-balanced scorecard using DEMATEL DEMATEL-based on ANP, and VIKOR [56]; (d) evaluating the performance factors of human resources involved in air traffic control using fuzzy graded mean integration representation (GMIR) and fuzzy additive ratio assessment method (ARAS-F) [57]; and (e) analyzing interrelationships and prioritizing the factors affecting sustainable intermodal freight using grey-DANP approach [58], among others.

Despite the viability of using the MCDM approach in assessing the interrelationships among factors, particularly in the air transport domain, it has not yet been applied in the context of the HPE concept, which satisfactorily covers a full range of factors influencing the performance of air traffic controllers. With the MCDM approach, the inherent relationships among factors can be better demonstrated according to the elicited judgment of subject matter experts, which previous methodologies failed to fulfill with the use of subjective survey questionnaires. Recognizing this significant limitation in the literature, this paper pioneers in developing a support system involving the MCDM approach, which extracts the interacting relationship among factors that influence the performance of air traffic controllers. This approach is designed to prioritize such factors in order to put forward relevant improvement measures in the general air traffic control scenario focused on highly prioritized factors. To illustrate the applicability of the proposed methodology, a case study is carried out in the Mactan Control Tower of the Civil Aviation Authority of the Philippines (CAAP).

In order to carry out such objectives, the most fitting MCDM approach points to DEMATEL and BWM. Individually, DEMATEL and BWM provide a significant contribution to the analysis of HPEs. For one, DEMATEL distinguishes the inherent characteristics of factors according to its classification being causal or effect criteria. For another, BWM provides weights of factors that can adequately shape its corresponding priority ranking. Recognizing the inherent characteristics of factors and their priority can sufficiently aid the decision-makers in strategy formulation and further policy initiatives by allocating efforts and resources to factors with high priority ranks. Furthermore, no other MCDM approach has a discriminating power, similar to DEMATEL, that can satisfactorily distinguish the characteristics of factors. While other MCDM approaches can also compute for weights of factors, such as ANP, BWM can provide a better perspective by considering both the best and worst criteria and analyzing the roster of factors with respect to these best and worst criteria. Additionally, due to the vagueness of human judgment, the fuzzy set theory is also integrated into the traditional DEMATEL and BWM in order to reflect the subjective nature of the decision-making process. The capability and synergy of DEMATEL, BWM, and fuzzy set theory can collectively advance an important part of the decision-making process of analyzing the factors involved in the HPE framework.

This paper proceeds with Section 2, which discusses an overview of the HPE factors that influence air traffic controllers' performance. Then Section 3 presents the MCDM tools currently used in general air transport operations. Next, Section 4 provides a brief discussion of the proposed MCDM methodology and the case study background. Section 5 then shows the proposed methodology's results and corresponding implications. Lastly, Section 6 presents the implications of the results and its research directions.

2. Human Performance Envelope (HPE) Components

With respect to aviation, human factors, and cognitive science literature, a comprehensive review of HPE components affecting operator performance and their corresponding dependencies is conducted [25,59,60]. The nine HPE components, also referred to as performance-shaping factors, are summarized as follows.

2.1. Workload

The mental workload resulting from the task loads expended externally, such as aircraft movements, weather, and rotation of laborers, is considered one of the most important factors influencing operator performance [18,26]. Correspondingly, the workload is perceived to be an emergent factor from the integration among various components, such as task requirements under specific circumstances, skills, behavior, and perceptions of operators [61]. In the context of air traffic control, the number of aircraft movements serves as a primary indicator of workload among other manifestations (e.g., weather) [18,62–67]. That is, an increase in workload (i.e., aircraft movements) and task difficulty may imply poor performance, as evidenced by low response accuracy and response latency. Other than the aircraft movement, other measurement tools include the uni-dimensional instantaneous self-assessment scale (ISA) [26,68], Bedford Workload Scale [69], and the National Aeronautics and Space Administration task load index (NASA-TLX) [58,67–71], air traffic workload input technique (ATWIT) [19,67], the hit-to-signal ratio on pointer deviations in gauge monitoring [27], and saccade durations [72], among others.

2.2. Situation Awareness (SA)

SA is defined as a three-level hierarchy construct involving the perception of elements in the environment within a volume of time and space, followed by the comprehension of their meaning, and lastly, the projection of their status in the near future [22]. In the cognitive science domain, SA is often used as a tool to assess the quality of human-machine interfaces such that a high level of SA corresponds to a properly designed interface and vice versa [73]. As a result of high SA, effective decision-making and high performance are maintained. However, in cases when there is a loss of SA, serious and even catastrophic consequences can occur [62]. In fact, 88% of aviation accidents in the commercial aviation industry are caused by human errors attributed to LSA [74]. Aside from the application of SA as a key concept that widely describes human performance in the air transportation system, it has also been used in other critical scenarios, the command and control room [75], sea-faring [76], land transportation [77], space traffic management [78], supply chain management [79], nuclear power plant [80], and healthcare [81], among others.

2.3. Communication

For communication, this factor involves the transfer of meaningful information from one entity to another and is independent of (but related to) language and speech [81–83]. For example, communications in air traffic control include radio and telephone, which often occurs simultaneously due to an increased air traffic volume [64–84]. Such exchange of information requires timeliness, accuracy, clarity, and receptiveness among the entities concerned. Some measurement tools for evaluating communication include TARGET, BOS, simulation study, direct observation, analysis of incident reports, and speech recordings, to name a few [24].

2.4. Teamwork

Teamwork, also termed crew resource management in the aviation industry, focuses on the proper response to threats to safety, including the proper management of errors committed by crew members [85]. Along with communication, teamwork requires close coordination between the team members and crew, even those outside the cockpit, to ensure aviation safety [86]. Otherwise, failure to communicate clearly can lead to a number of major accidents. Therefore, relevant error management training is strongly imposed

to address several functions in teamwork, which relates to coordinating in a proactive sense, cross-checking members, and backing them up during phases that require a high workload [87]. When teams are in a safe and efficient environment to perform their tasks in the air traffic services, team resource management (TRM) aids in avoiding serious incidents and accidents resulting from inadequate teamwork [88].

2.5. Trust

Trust typically covers two constructs: dispositional trust and situational trust [89]. Between the two constructs, the use of the term ‘trust’ in the aviation industry leans more toward situational trust, specifically in the use of automation, also referred to as human-machine trust. As greater utilization of automation tools is perceived to aid in the tasks of air traffic controllers, the dynamic expectation of machine reliability continues to affect the operator’s trust in an automated system [90]. Although made to support and fully benefit air traffic control operations such as conflict and flight anomaly detection [27,91], the level of automation imposed in the control room can also present many disadvantages, particularly a loss of controller SA due to the exclusion of human in the system control loops [92,93]. According to [27], automation applied to information processing functions may not necessarily support successful controller clearing of aircraft. In most conditions, it is dependent on the order level of information processing functions in which automation is embedded. Similarly, [28] noted that while a remote air traffic control system can supply air traffic services to airports by enabling communication, navigational support, and surveillance from a remote location, it can also pose serious challenges to traditional air traffic operations, including coordination among controllers and control during increased traffic volume and multiple airports. In short, introducing automation to air traffic control promotes a human-outside-the-loop system which, in particular, offloads controllers in their manual task loads resulting in a general loss of SA [27]. That is, as increased air traffic control tasks are performed via automation, air traffic controllers become less aware of the system as a whole. Moreover, [26] also reported that SA is reduced in most automated conditions which are responsible for dominant air traffic control tasks such as conflict detection and decision-making. Nevertheless, tasks carried out in most automated conditions imply less workload on air traffic controllers.

2.6. Fatigue

In the context of the International Civil Aviation Organization (ICAO), fatigue is defined as “the physiological state of reduced mental or physical performance capability resulting from sleep loss or extended wakefulness, circadian phase, or workload (mental and/or physical activity) that can impair a crew member’s alertness and ability to safely operate an aircraft or perform safety-related duties” [94]. Since fatigue and other states, such as drowsiness, may be considered similar in terms of neurophysiological characterization, there exists a difficulty in distinguishing one from the other. To measure fatigue, subjective and objective tools are deployed according to the type of fatigue one is concerned with examining (e.g., severity, physical fatigue, and the overall extent of fatigue) [95]. Such tools include, but are not limited to, self-reported measures (e.g., Samn–Perelli fatigue scale, sleep logs) [68,95–98], OHCS urine test, heart rate, vanillyl mandelic acid (VMA) excretion, simple auditory reaction time, critical flicker fusion, oral temperature, event-related potential (ERP), cortisol, electroencephalogram (EEG) and electro-oculogram (EOG), tapping test, grid tapping test, pupil diameter, and physiological tests (e.g., flicker fusion threshold, response stick, near point, thumb/index finger strength, systolic and diastolic pressure) [16,71,96,98,99].

2.7. Stress

Stress in jobs is specifically a result of work settings that come from various factors such as work tasks, workplace, job characteristics, role conflict, and worker capabilities [84]. In the dynamic nature of air traffic control, which demands multiple safety decisions in

quick succession, the stress of air traffic controllers results in fatigue, affecting their professional capabilities, responsiveness, and vigilance. Among air traffic controllers, particularly enroute controllers, several contributory activities such as situation monitoring, managing air traffic sequences, resolving aircraft conflicts, routing or planning of flights, managing sector/position resources, and assessing weather impact are identified to have caused stress in the workplace [100]. In this line, the need to establish stress coping strategies (e.g., compartmentalization, cognitive behavioral therapy, recovery context indicator) becomes necessary to reactivate air traffic controllers quickly, effectively, and sustainably [101]. Furthermore, several approaches have been developed in the literature to measure stress, including the occupational stress indicator (OSI) [102], stress diagnostic survey (SDS) [103], and exploratory and confirmatory factor analysis (EFA & CFA) [104].

2.8. Attention and Vigilance

Attention is defined as the ability to attend to information or any stimulus in the environment, while vigilance is the representation of sustained attention over a considerably prolonged period [105]. In the nature of air traffic controllers' jobs, it is extremely necessary to combat lapses in sustained attention to avoid severe or even deadly consequences. Unfortunately, for vigilance, any lapse can only be noted after a mistake attributed to such lapse occurs [106]. In such conditions, it is difficult to directly measure operators' performance or cognitive states in any working environment. For instance, errors of perception in empirical research work are found to be associated with a loss of vigilance as manifested by failure to monitor non-salient stimuli (e.g., aircraft's climb rate) [107].

3. MCDM in Air Transport Operations

3.1. Fuzzy Set Theory

Traditional MCDM methods such as DEMATEL and BWM are transformed into their fuzzy counterpart in recognition of the subjective nature of judgment among humans. With fuzzy set theory, technically known as fuzziness, vagueness is handled well by capturing the decision makers' judgment (e.g., imprecise goals, constraints, and actions) and presenting such judgment into fuzzy numbers [108]. In the case of HPE components, examining the relationship among factors involves subjective functions (e.g., SA, communication, trust) that cannot be directly represented by a numerical value. Thus, the use of fuzzy logic becomes appropriate in this context to ensure that any subjectivity in the assessment of each factor is considered. A detailed discussion of the fundamental theory of fuzzy set is discussed by [109], while some of its basic concepts are presented as follows:

Let X be a universal set where $A \subseteq X$. A is considered a standard fuzzy set if $\exists$ a membership function $\mu_A(x)$ where $\mu_A(x) : X \rightarrow [0, 1]$. In a set of 2-tuple, $A = \{x, \mu_A(x) : x \in X, \mu_A(x) \in [0, 1]\}$ is a fuzzy set where $x \in A$ and $\mu_A(x)$ is a membership function of $x \in A$. In the case of a triangular fuzzy number (TFN), a triplet $\tilde{A} = (l, m, r)$ and a membership function $\mu_A(x)$ can be defined as follows (see Equation (1)):

$$\mu_A(x) = \begin{cases} 0 & x < l \\ (x-l)/(m-l) & l \leq x < m \\ (r-l)/(r-m) & m \leq x \leq r \\ 0 & x > r \end{cases} \quad (1)$$

where l, m, r are real numbers being $l, m, r \in R$, $\mu_A(x) \rightarrow [0, 1]$ and X is the universe of discourse. The fuzzy logic has been widely integrated over the years into MCDM approaches such as AHP, TOPSIS, and DEMATEL, to name a few.

3.2. Decision-Making Trial Evaluation and Laboratory (DEMATEL)

The DEMATEL methodology was first introduced at the Battelle Memorial Institute of Geneva Research Center, which aims to extract the relation between criteria from a complex system [32]. With DEMATEL, the interrelation among criteria is illustrated better as its corresponding classification (i.e., causal or effect) is established. Furthermore, DEMATEL

is able to develop an interrelationship network digraph showing the structural relationship among factors along with the strength of influence evident among criteria. The process of evaluating the relationship among HPE components can be formulated as an MCDM problem, which can be represented suitably with the use of the DEMATEL methodology. As an extension to the classical DEMATEL methodology, it has been successfully combined with other MCDM tools, such as ANP and BWM, to advance the application of such tools into the complex decision-making process of evaluating criteria.

3.3. Best-Worst Method (BWM)

One of the most recent advances in the field of MCDM is the development of the best-worst method (BWM) in 2015 [36]. Here, the weights of criteria and alternatives with respect to a defined criterion (i.e., the best and the worst) based on pairwise comparisons can be obtained sufficiently. Unlike prior MCDM tools, the BWM only performs reference comparisons that consider the preference of a criterion (i.e., best criterion) over other criteria and the preference of all other criteria over another (i.e., worst criterion). As such, the BWM effectively removes the inconsistency evident from the pairwise comparisons and renders it more accurate and easier to perform. Despite its infancy as an MCDM tool, the BWM has already been widely adopted, singly or together with other tools, to address various practical issues in the literature and has proved to be significantly viable.

3.4. Proposed Fuzzy DEMATEL-Based BWM

This section presents the implementation of the proposed fuzzy DEMATEL-based BWM to evaluate the HPE components in the air transport industry. In the context of this paper, an expert team of air traffic controllers' shift supervisors consisting of six specialists serves as decision-makers in the assessment of HPE components. These supervisors have been serving at the Mactan Control Tower of CAAP and are considered credible sources concerning their areas of expertise.

Step 1: Compute for initial direct-relation fuzzy matrices.

The initial direct-relation fuzzy matrix ($\tilde{E}^k$) for each decision-maker is obtained as in Equation (2). Here, the decision-makers elicit their judgment on the influence of criterion i to criterion j using the linguistic scales in Table 1 according to [109], where K denotes the number of decision-makers.

$$\tilde{E}^k = \begin{bmatrix} 0 & \cdots & \tilde{e}_{1n}^k \\ \vdots & \ddots & \vdots \\ \tilde{e}_{n1}^k & \cdots & 0 \end{bmatrix}, K = 1, 2, \dots, p \quad (2)$$

Table 1. Linguistic scales for the pairwise evaluation of decision criteria.

Linguistic Term	Membership Function
No influence (NI)	(0.00, 0.00, 0.25)
Very low influence (VLII)	(0.00, 0.25, 0.50)
Low influence (LI)	(0.25, 0.50, 0.75)
High influence (HI)	(0.50, 0.75, 1.00)
Very high influence (VHI)	(0.75, 1.00, 1.00)

Step 2: Generate the aggregated direct-relation fuzzy matrix.

The initial direct-relation fuzzy matrix of K decision-makers is aggregated using Equation (3) to arrive at the matrix $\tilde{E} = [\tilde{e}_{ij}]$ where $[\tilde{e}_{ij}] = (l_{ij}, m_{ij}, u_{ij})$.

$$\tilde{E} = \frac{\tilde{E}^1 + \tilde{E}^2 + \dots + \tilde{E}^K}{K} \quad (3)$$

Step 3: Calculate normalized direct-relation fuzzy matrix.

The direct-relation fuzzy matrix is normalized in Equations (4)–(7). Here, the normalized fuzzy direct-relation matrix is represented by the matrix $\tilde{F}$

$$\tilde{F} = \frac{\tilde{E}}{\gamma} \quad (4)$$

$$\gamma = \max \sum_{j=1}^n u_j \quad (5)$$

$$\tilde{F} = \begin{bmatrix} \tilde{f}_{11} & \cdots & \tilde{f}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{f}_{n1} & \cdots & \tilde{f}_{nn} \end{bmatrix} \quad (6)$$

$$\tilde{f}_{ij} = \frac{\tilde{e}_{ij}}{\gamma} = \left(\frac{l_{ij}}{\gamma}, \frac{m_{ij}}{\gamma}, \frac{u_{ij}}{\gamma} \right) \quad (7)$$

Step 4: Calculate the total-relation fuzzy matrix.

In this step, the total-relation fuzzy matrix, $\tilde{T}$, is computed as in Equations (8)–(12), where I is an identity matrix.

$$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} & \cdots & \tilde{t}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{t}_{n1} & \cdots & \tilde{t}_{nn} \end{bmatrix} \quad (8)$$

$$\tilde{t}_{ij} = \left(l'_{ij}, m'_{ij}, u'_{ij} \right) \quad (9)$$

$$\text{Matrix} \begin{bmatrix} l'_{ij} \end{bmatrix} = F_l \times (I - F_l)^{-1} \quad (10)$$

$$\text{Matrix} \begin{bmatrix} m'_{ij} \end{bmatrix} = F_m \times (I - F_m)^{-1} \quad (11)$$

$$\text{Matrix} \begin{bmatrix} u'_{ij} \end{bmatrix} = F_u \times (I - F_u)^{-1} \quad (12)$$

Step 5: Transform the total-relation fuzzy matrix into a total-relation crisp matrix.

The total-relation fuzzy matrix, $\tilde{T}$, is converted into a total-relation crisp matrix represented by T using Equation (13).

$$t_{ij} = \frac{1}{4} \left(l'_{ij} + 2m'_{ij} + u'_{ij} \right) \quad (13)$$

Step 6: Compute cause-effect vectors using the matrix components of the total-relation crisp matrix.

Following the matrix components of matrix T , vectors r and s can be computed using Equation (14) and Equation (15), respectively. Vectors r and s represent the sum of the rows and columns of matrix T . Each criterion can be classified as a causal criterion or an effect criterion based on the following relations: when $(r_i - s_i)$ is positive, criterion i is considered to be under the causal cluster; otherwise, it falls under the effect cluster. An influential network relations map can also be generated by mapping the data set of $(r_i + s_i, r_i - s_i)$.

$$r = \left[\sum_{j=1}^n t_{ij} \right]_{n \times 1} \quad (14)$$

$$s = \left[\sum_{j=1}^n t_{ij} \right]_{1 \times n} \quad (15)$$

Step 7: Proceed with the DEMATEL methodology beginning with the identification of the best and worst criteria among a set of decision criteria representing the HPE components.

The decision-makers elicit their judgment by selecting the best criterion (most important) and the worst criterion (least important) among the HPE components. The best criterion is denoted as c_B while the worst criterion as c_W .

Step 8: Perform the fuzzy reference comparisons for the best criterion.

The best criterion chosen by the decision-makers is evaluated with respect to other criteria such that a fuzzy reference comparison is represented as $\tilde{a}_{ij}$ with i being the best criterion while j is the other criterion. Using the natural language listed in Table 2, the fuzzy preference of the best criterion over other criteria can be identified as the fuzzy best-to-others vector, $\tilde{A}_B$, as in Equation (16):

$$\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots, \tilde{a}_{Bn}) \quad (16)$$

Table 2. Linguistic scales for the evaluation of decision criteria.

Linguistic Term	Membership Function
Equally important (EI)	(1, 1, 1)
Weakly important (WI)	(2/3, 1, 3/2)
Fairly important (FI)	(3/2, 2, 5/2)
Very important (VI)	(5/2, 3, 7/2)
Absolutely important (AI)	(7/2, 4, 9/2)

Step 9: Perform the fuzzy reference comparisons for the worst criterion.

Similar to the previous step, a fuzzy reference comparison is executed between the other criteria and the worst criterion chosen by the decision-makers. Here, the fuzzy reference comparison represents the others-to-worst vector, $\tilde{A}_W$, using the natural language listed in Table 1 (see Equation (17)).

$$\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW}) \quad (17)$$

Step 10: Solve for the optimal fuzzy weights.

The optimal fuzzy weight $(\tilde{w}_1^*, \tilde{w}_2^*, \dots, \tilde{w}_n^*)$ for each criterion is, for each fuzzy pair $\tilde{w}_B/\tilde{w}_j$ and $\tilde{w}_j/\tilde{w}_W$, should have $\tilde{w}_B/\tilde{w}_j = \tilde{a}_{Bj}$ and $\tilde{w}_j/\tilde{w}_W = \tilde{a}_{jW}$. In order to satisfy such conditions for all j , a solution where the maximum absolute gaps $\left| \frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{a}_{Bj} \right|$ and $\left| \frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{a}_{jW} \right|$ for all j minimized should be computed. While the traditional BWM involves crisp numbers instead of triangular fuzzy numbers, as in this case, the weights of each criterion are represented as $\tilde{w}_j = (l_j^w, m_j^w, u_j^w)$. Furthermore, GMIR is employed as a defuzzification method (see Equation (18)) where $\tilde{a}_i = (l_i, m_i, u_i)$ and the GMIR $R(\tilde{a}_i)$. To obtain the optimal fuzzy weights and the optimal value of $\tilde{\xi}$ referred to as $\tilde{\xi}^*$, Equation (19) is solved considering the relations of the triangular fuzzy set $l^{\xi} \leq m^{\xi} \leq u^{\xi}$ and $\tilde{\xi}^* = (k^*, k^*, k^*), k^* \leq l^{\xi}$:

$$R(\tilde{a}_i) = \frac{l_i + 4m_i + u_i}{6} \quad (18)$$

$$\begin{aligned} & \min \tilde{\xi}^* \\ & \text{subject to:} \\ & \left\{ \begin{array}{l} \left| \frac{l_B^w m_B^w u_B^w}{l_j^w m_j^w u_j^w} - (l_{Bj} m_{Bj} u_{Bj}) \right| \leq (k^*, k^*, k^*) \\ \left| \frac{l_j^w m_j^w u_j^w}{l_W^w m_W^w u_W^w} - (l_{jW} m_{jW} u_{jW}) \right| \leq (k^*, k^*, k^*) \\ \sum_{j=1}^n R(\tilde{w}_j) = 1 \\ l_j^w \leq m_j^w \leq u_j^w \\ l_j^w \geq 0 \\ j = 1, 2, \dots, n \end{array} \right. \quad (19) \end{aligned}$$

Following the definition of a consistency degree of fuzzy pairwise comparisons according to [110], a fuzzy comparison is considered to be fully consistent when $\tilde{a}_{Bj} \times \tilde{a}_{jW} = \tilde{a}_{BW}$. Recall that $\tilde{a}_{Bj}$ is the fuzzy preference of the best criterion over criterion j , $\tilde{a}_{jW}$ is the fuzzy preference of criterion j over the worst criterion, and $\tilde{a}_{BW}$ is the fuzzy preference of the best criterion over the worst criterion. For a comprehensive presentation of the constrained optimization problem for calculating the optimal fuzzy weights, its corresponding nonlinear constrained optimization problem, and consistency ratio (CR) for fuzzy BWM, please see [110]. The consistency index (CI) for fuzzy BWM is shown in Table 3, which serves as an input in computing the CR using Equation (20):

$$CR = \frac{\tilde{\xi}^*}{CI} \quad (20)$$

Table 3. Linguistic scales for the evaluation of decision criteria [36].

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency index ξ	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

A CR value close to zero indicates high consistency among the elicited judgment of decision-makers.

4. Results and Discussion

Illustrative Case Study

MCIA is one of the most important airport transportation hubs in the southern area of the Philippines and is situated in Lapu-Lapu City, Mactan Island, province of Cebu. MCIA also acts as the country's secondary primary international entry point. Since then, as Cebu, the Queen City of the South, has grown to be a popular tourist destination for both domestic and international travelers, the airport has been a source of economic growth for the nation. The Mactan-Cebu International Airport Authority (MCIAA) reported a 13% annual passenger increase over the previous ten years, demonstrating the rising demand for air travel. However, because of the frequent airline delays, the demand is typically met with complaints. The MCIAA, along with Mactan Control Tower's airline and air traffic management, are faced with meeting the demands of the increasing volume of flight passengers while maintaining schedule reliability. Furthermore, these stakeholders also collaborate to address air traffic congestion as it occurs. Note that air traffic management plays a crucial role in carrying out the ATFM actions among other stakeholders whose interests focus on minimizing operating costs and maximizing the utilization of resources [111,112].

Therefore, this paper centers on evaluating the performance-shaping factors that affect the efficiency of air traffic controllers. The performance-shaping factors represent the decision criteria considered in this paper. Such factors are denoted as C1 for 'workload,' C2 for 'situation awareness,' C3 for 'communication,' C4 for 'teamwork,' C5 for 'trust,' C6 for 'fatigue,' C7 for 'stress,' C8 for 'vigilance,' and C9 for 'attention.' Following the fuzzy DEMATEL and fuzzy BWM methods, decision-makers in air traffic management are tasked to elicit judgment using the linguistic expressions presented in Table 4. For illustration purposes, take the results from the assessment of expert 1. First, the decision criteria are evaluated pairwise in terms of its relational impact being 'no influence,' 'very low influence,' 'low influence,' 'high influence,' and 'very high influence' (see Table 1). Then, the equivalent fuzzy numbers corresponding to each linguistic scale are indicated in Table 5. Once the fuzzy numbers are set, the individual judgment of each decision-maker is aggregated, as shown in Table 6 using Equation (3). The aggregated matrix is then normalized by Equation (4), with results listed in Table 7. The total relations matrix is obtained via Equation (8), as presented in Table 8. To further evaluate the criteria classification as causal or effect, the elements of the total relations matrix are defuzzified using Equation (13). As a result, the defuzzified values are then obtained, as shown in Table 9. Note that there are matrix elements highlighted in grey, which represent significant relations among criteria. For instance, in C1, all matrix elements corresponding to C1 through C9, except C6, are highlighted, which implies that C1 significantly impacts all criteria except C6. A visual representation of these influential relations is reflected in Figure 1. These crisp values are then processed to distinguish the classifications of criteria. A final output of the fuzzy DEMATEL method is shown in Table 10, where the criteria are classified according to the inherent nature it contributes to the decision-making process.

Table 4. Sample pairwise evaluation of one decision-maker according to the fuzzy DEMATEL method.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	NI	VHI	HI	VHI	HI	HI	VHI	HI	VHI
C2	HI	NI	HI	HI	HI	HI	HI	VHI	HI
C3	HI	HI	NI	HI	HI	VHI	VHI	HI	HI
C4	HI	HI	HI	NI	VHI	LI	LI	HI	HI
C5	VHI	HI	VHI	HI	NI	HI	VHI	HI	HI
C6	VHI	HI	VHI	HI	LI	NI	HI	LI	LI
C7	LI	HI	HI	LI	LI	LI	NI	HI	LI
C8	VHI	LI	VHI	LI	LI	HI	LI	NI	HI
C9	LI	HI	HI	LI	LI	LI	LI	LI	NI

Table 5. Corresponding fuzzy numbers of the pairwise evaluation among criteria.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	(0.00, 0.00, 0.25)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)
C2	(0.50, 0.75, 1.00)	(0.00, 0.00, 0.25)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)
C3	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.00, 0.25)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
C4	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.00, 0.25)	(0.75, 1.00, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
C5	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.00, 0.25)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
C6	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.00, 0.00, 0.25)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)
C7	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.00, 0.00, 0.25)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
C8	(0.75, 1.00, 1.00)	(0.25, 0.50, 0.75)	(0.75, 1.00, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.00, 0.00, 0.25)	(0.50, 0.75, 1.00)
C9	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.00, 0.00, 0.25)

Table 6. Aggregated relational impact among criteria in triangular fuzzy numbers representing the direct-influence matrix G .

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	(0.00, 0.00, 0.25)	(0.71, 0.96, 1.00)	(0.67, 0.92, 1.00)	(0.63, 0.88, 1.00)	(0.58, 0.83, 1.00)	(0.63, 0.88, 1.00)	(0.75, 1.00, 1.00)	(0.63, 0.88, 1.00)	(0.71, 0.96, 1.00)
C2	(0.63, 0.88, 1.00)	(0.00, 0.00, 0.25)	(0.50, 0.75, 0.92)	(0.63, 0.88, 1.00)	(0.58, 0.83, 1.00)	(0.54, 0.79, 0.96)	(0.54, 0.79, 0.96)	(0.67, 0.92, 1.00)	(0.71, 0.96, 1.00)
C3	(0.67, 0.92, 1.00)	(0.67, 0.92, 1.00)	(0.00, 0.00, 0.25)	(0.58, 0.83, 1.00)	(0.63, 0.88, 1.00)	(0.38, 0.63, 0.83)	(0.46, 0.71, 0.88)	(0.58, 0.83, 1.00)	(0.63, 0.88, 1.00)
C4	(0.50, 0.75, 0.96)	(0.67, 0.92, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.00, 0.25)	(0.71, 0.96, 1.00)	(0.33, 0.54, 0.79)	(0.29, 0.50, 0.75)	(0.54, 0.79, 0.96)	(0.58, 0.83, 1.00)
C5	(0.71, 0.96, 1.00)	(0.58, 0.83, 1.00)	(0.67, 0.92, 1.00)	(0.54, 0.79, 0.96)	(0.00, 0.00, 0.25)	(0.33, 0.50, 0.75)	(0.71, 0.96, 1.00)	(0.54, 0.75, 0.88)	(0.58, 0.83, 1.00)
C6	(0.67, 0.92, 1.00)	(0.50, 0.75, 0.96)	(0.50, 0.71, 0.83)	(0.42, 0.67, 0.92)	(0.29, 0.46, 0.71)	(0.00, 0.00, 0.25)	(0.63, 0.88, 1.00)	(0.42, 0.63, 0.83)	(0.42, 0.63, 0.83)
C7	(0.42, 0.67, 0.83)	(0.63, 0.88, 1.00)	(0.63, 0.88, 1.00)	(0.54, 0.79, 0.96)	(0.42, 0.63, 0.83)	(0.42, 0.67, 0.92)	(0.00, 0.00, 0.25)	(0.54, 0.79, 1.00)	(0.58, 0.83, 0.96)
C8	(0.75, 1.00, 1.00)	(0.50, 0.75, 0.92)	(0.75, 1.00, 1.00)	(0.58, 0.83, 0.92)	(0.42, 0.67, 0.92)	(0.42, 0.67, 0.92)	(0.33, 0.58, 0.83)	(0.00, 0.00, 0.25)	(0.58, 0.83, 1.00)
C9	(0.42, 0.63, 0.83)	(0.63, 0.88, 1.00)	(0.54, 0.79, 1.00)	(0.50, 0.75, 0.96)	(0.42, 0.67, 0.88)	(0.33, 0.58, 0.83)	(0.46, 0.71, 0.88)	(0.54, 0.79, 0.96)	(0.00, 0.00, 0.25)

Table 7. Normalized direct-influence matrix X .

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	(0.00, 0.00, 0.03)	(0.09, 0.12, 0.12)	(0.08, 0.11, 0.12)	(0.08, 0.11, 0.12)	(0.07, 0.10, 0.12)	(0.08, 0.11, 0.12)	(0.09, 0.12, 0.12)	(0.08, 0.11, 0.12)	(0.09, 0.12, 0.12)
C2	(0.08, 0.11, 0.12)	(0.00, 0.00, 0.03)	(0.06, 0.09, 0.11)	(0.08, 0.11, 0.12)	(0.07, 0.10, 0.12)	(0.07, 0.10, 0.12)	(0.07, 0.10, 0.12)	(0.08, 0.11, 0.12)	(0.09, 0.12, 0.12)
C3	(0.08, 0.11, 0.12)	(0.08, 0.11, 0.12)	(0.00, 0.00, 0.03)	(0.07, 0.10, 0.12)	(0.08, 0.11, 0.12)	(0.05, 0.08, 0.10)	(0.06, 0.09, 0.11)	(0.07, 0.10, 0.12)	(0.08, 0.11, 0.12)
C4	(0.06, 0.09, 0.12)	(0.08, 0.11, 0.12)	(0.06, 0.09, 0.12)	(0.00, 0.00, 0.03)	(0.09, 0.12, 0.12)	(0.04, 0.07, 0.10)	(0.04, 0.06, 0.09)	(0.07, 0.10, 0.12)	(0.07, 0.10, 0.12)
C5	(0.09, 0.12, 0.12)	(0.07, 0.10, 0.12)	(0.08, 0.11, 0.12)	(0.07, 0.10, 0.12)	(0.00, 0.00, 0.03)	(0.04, 0.06, 0.09)	(0.09, 0.12, 0.12)	(0.07, 0.09, 0.11)	(0.07, 0.10, 0.12)
C6	(0.08, 0.11, 0.12)	(0.06, 0.09, 0.12)	(0.06, 0.09, 0.1)	(0.05, 0.08, 0.11)	(0.04, 0.06, 0.09)	(0.00, 0.00, 0.03)	(0.08, 0.11, 0.12)	(0.05, 0.08, 0.10)	(0.05, 0.08, 0.10)
C7	(0.05, 0.08, 0.10)	(0.08, 0.11, 0.12)	(0.08, 0.11, 0.12)	(0.07, 0.10, 0.12)	(0.05, 0.08, 0.10)	(0.05, 0.08, 0.11)	(0.00, 0.00, 0.03)	(0.07, 0.10, 0.12)	(0.07, 0.10, 0.12)
C8	(0.09, 0.12, 0.12)	(0.06, 0.09, 0.11)	(0.09, 0.12, 0.12)	(0.07, 0.10, 0.11)	(0.05, 0.08, 0.11)	(0.05, 0.08, 0.11)	(0.04, 0.07, 0.10)	(0.00, 0.00, 0.03)	(0.07, 0.10, 0.12)
C9	(0.05, 0.08, 0.10)	(0.08, 0.11, 0.12)	(0.07, 0.10, 0.12)	(0.06, 0.09, 0.12)	(0.05, 0.08, 0.11)	(0.04, 0.07, 0.10)	(0.06, 0.09, 0.11)	(0.07, 0.10, 0.12)	(0.00, 0.00, 0.03)

Table 8. Total-influential matrix.

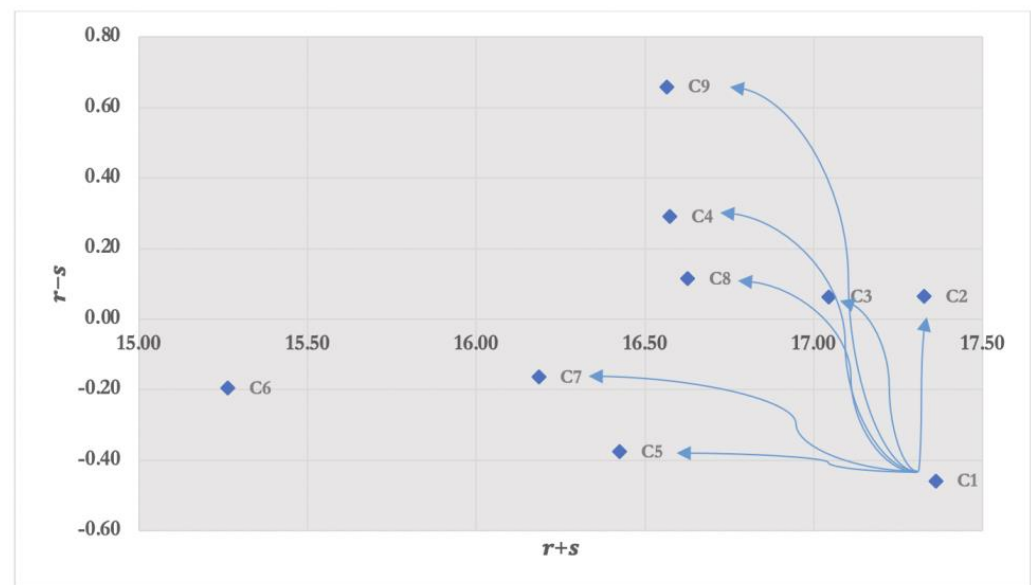
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	(0.10, 0.38, 2.84)	(0.18, 0.50, 3.01)	(0.17, 0.48, 2.97)	(0.16, 0.47, 2.96)	(0.15, 0.44, 2.84)	(0.14, 0.4, 2.72)	(0.17, 0.46, 2.81)	(0.16, 0.46, 2.93)	(0.18, 0.49, 2.99)
C2	(0.16, 0.45, 2.88)	(0.09, 0.37, 2.87)	(0.15, 0.44, 2.91)	(0.15, 0.44, 2.90)	(0.14, 0.41, 2.79)	(0.13, 0.38, 2.67)	(0.14, 0.42, 2.76)	(0.16, 0.45, 2.88)	(0.17, 0.47, 2.93)
C3	(0.16, 0.45, 2.84)	(0.16, 0.46, 2.92)	(0.08, 0.35, 2.80)	(0.15, 0.43, 2.87)	(0.15, 0.41, 2.75)	(0.11, 0.35, 2.62)	(0.13, 0.40, 2.72)	(0.15, 0.43, 2.84)	(0.16, 0.45, 2.90)
C4	(0.13, 0.41, 2.76)	(0.15, 0.43, 2.84)	(0.13, 0.41, 2.80)	(0.07, 0.31, 2.70)	(0.15, 0.40, 2.68)	(0.10, 0.32, 2.54)	(0.10, 0.36, 2.63)	(0.14, 0.40, 2.76)	(0.15, 0.42, 2.82)
C5	(0.17, 0.45, 2.8)	(0.16, 0.45, 2.88)	(0.16, 0.45, 2.84)	(0.14, 0.42, 2.82)	(0.08, 0.31, 2.63)	(0.10, 0.34, 2.58)	(0.16, 0.43, 2.69)	(0.14, 0.42, 2.79)	(0.15, 0.45, 2.86)
C6	(0.15, 0.4, 2.64)	(0.13, 0.39, 2.71)	(0.13, 0.38, 2.66)	(0.12, 0.37, 2.66)	(0.10, 0.33, 2.53)	(0.05, 0.24, 2.37)	(0.13, 0.38, 2.54)	(0.12, 0.36, 2.63)	(0.12, 0.38, 2.67)
C7	(0.13, 0.4, 2.75)	(0.15, 0.43, 2.85)	(0.15, 0.42, 2.81)	(0.13, 0.40, 2.79)	(0.12, 0.37, 2.67)	(0.10, 0.34, 2.57)	(0.07, 0.30, 2.58)	(0.14, 0.40, 2.77)	(0.15, 0.42, 2.82)
C8	(0.17, 0.45, 2.77)	(0.14, 0.43, 2.84)	(0.17, 0.45, 2.81)	(0.14, 0.42, 2.79)	(0.12, 0.38, 2.68)	(0.11, 0.35, 2.57)	(0.11, 0.38, 2.65)	(0.08, 0.32, 2.69)	(0.15, 0.44, 2.83)
C9	(0.12, 0.38, 2.70)	(0.14, 0.42, 2.79)	(0.13, 0.4, 2.76)	(0.13, 0.38, 2.74)	(0.11, 0.36, 2.62)	(0.09, 0.32, 2.51)	(0.12, 0.36, 2.60)	(0.13, 0.39, 2.72)	(0.07, 0.31, 2.69)

Table 9. Defuzzified total influential matrix.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0.92	1.05	1.03	1.01	0.97	0.91	0.98	1.01	1.04
C2	0.99	0.92	0.99	0.99	0.94	0.89	0.93	0.98	1.01
C3	0.97	1.00	0.90	0.97	0.93	0.86	0.91	0.96	0.99
C4	0.93	0.96	0.94	0.85	0.91	0.82	0.86	0.92	0.95
C5	0.97	0.98	0.98	0.95	0.83	0.84	0.92	0.94	0.98
C6	0.90	0.91	0.89	0.88	0.82	0.73	0.86	0.87	0.89
C7	0.91	0.97	0.95	0.93	0.88	0.84	0.81	0.93	0.95
C8	0.96	0.96	0.97	0.94	0.89	0.84	0.88	0.85	0.96
C9	0.90	0.94	0.92	0.91	0.86	0.81	0.86	0.91	0.85

Table 10. Influences given (and received) by (and on) each criterion.

Criteria	r	s	$r-s$	$r+s$	Cluster
C1	8.45	8.91	−0.46	17.36	Effect
C2	8.70	8.63	0.06	17.33	Causal
C3	8.55	8.49	0.06	17.05	Causal
C4	8.43	8.14	0.29	16.57	Causal
C5	8.02	8.40	−0.38	16.42	Effect
C6	7.53	7.73	−0.20	15.26	Effect
C7	8.01	8.17	−0.16	16.19	Effect
C8	8.37	8.26	0.12	16.63	Causal
C9	8.61	7.95	0.66	16.56	Causal

**Figure 1.** Influential network relations map (sample for C1).

Aside from classifying the nature of each criterion, the fuzzy BWM approach is carried out to obtain its priority vector. To begin with, the decision-makers are delegated to select the best and worst criterion among the set of criteria given. Take, for instance, the evaluation of one decision-maker. The best criterion is selected as ‘teamwork’ while the worst criterion is ‘stress.’ The best criterion is evaluated with respect to another criterion with a linguistic expression shown in Table 2. On the other hand, the other criterion is also evaluated against the worst criterion. These evaluations on the best-to-others and others-to-worst are presented in Tables 11 and 12, respectively. Note that these linguistic expressions have their corresponding fuzzy numbers, which are then embedded into the model shown in Equation (19). Then, by solving Equation (19), the optimal value is obtained along with the optimal fuzzy weights of each criterion (see, for example, Table 13). After generating the optimal fuzzy weights of all decision-makers, their corresponding crisp values are generated, as shown in Table 14. Then, the aggregated optimal fuzzy weights are obtained by solving for the normalized arithmetic mean of the entire set of optimal fuzzy weights. This aggregated optimal fuzzy weight and the CR are shown in Tables 15 and 16, respectively. It can be noted that an average CR of 0.2417 is a good indication that the judgment elicited by decision-makers is rather consistent, given that it is close to 0.

Table 11. Best-to-others fuzzy reference comparisons.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	VI	EI	VI	VI	VI	EI	EI	EI	VHI
C2	AI	EI	AI	FI	FI	AI	AI	AI	HI
C3	AI	EI	EI	EI	EI	EI	EI	EI	HI
C4	VI	EI	AI	AI	VI	EI	VI	VI	HI
C5	VI	VI	VI	VI	VI	WI	WI	VI	HI
C6	VI	VI	VI	VI	VI	VI	VI	VI	LI
C7	LI	HI	HI	LI	LI	LI	NI	HI	LI
C8	VHI	LI	VHI	LI	LI	HI	LI	NI	HI
C9	LI	HI	HI	LI	LI	LI	LI	LI	NI

Table 12. Others-to-best fuzzy reference comparisons.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	FI	FI	VI	EI	WI	FI	FI	FI	VI
C2	FI	FI	VI	EI	WI	FI	FI	FI	VI
C3	FI	FI	VI	FI	WI	FI	FI	FI	VI
C4	FI	EI	VI	EI	WI	FI	FI	EI	VI
C5	FI	VI	VI	FI	WI	FI	FI	VI	VI
C6	FI	FI	VI	FI	WI	FI	FI	FI	VI
C7	FI	VI	VI	FI	EI	FI	FI	VI	VI
C8	FI	FI	VI	FI	WI	FI	FI	FI	VI
C9	FI	FI	VI	EI	WI	FI	FI	FI	VI

Table 13. Fuzzy optimal weights.

Criteria	l	m	u
C1	0.1064358	0.1064358	0.1064358
C2	0.0591310	0.0591310	0.0591310
C3	0.0591310	0.0591310	0.0591310
C4	0.1708869	0.2278492	0.2660894
C5	0.1064358	0.1139246	0.1139246
C6	0.0591310	0.0591310	0.0591310
C7	0.1064358	0.1139246	0.1139246
C8	0.1330447	0.1330447	0.1330447
C9	0.1330447	0.1330447	0.1330447

Table 14. Crisp optimal weights.

Criteria	Weights
C1	0.10644
C2	0.05913
C3	0.05913
C4	0.22473
C5	0.11268
C6	0.05913
C7	0.11268
C8	0.13304
C9	0.13304

Table 15. Aggregated weights of criteria.

Criteria	Weights
C1	0.1022
C2	0.0994
C3	0.1436
C4	0.1112
C5	0.0836
C6	0.1232
C7	0.1198
C8	0.1130
C9	0.1197

Table 16. Consistency ratio of each decision-makers evaluation.

Expert	Best-Worst	Rating	CI	$\tilde{\xi}^*$	CR
1	C2-C5	FI	5.2900	0.5505	0.1041
2	C2-C4	AI	8.0400	2.0000	0.2488
3	C1-C5	EI	3.0000	1.7639	0.5880
4	C3-C9	VI	6.6900	1.0000	0.1495
5	C4-C7	VI	6.6900	1.0000	0.1495
6	C2-C9	VI	6.6900	1.4062	0.2102

5. Managerial Implications

The application of fuzzy DEMATEL and fuzzy BWM to evaluate the performance-shaping factors of air traffic controllers has produced interesting results on the nature of such factors and their priority vector. Firstly, a key result of the fuzzy DEMATEL methodology pointed out that the performance-shaping factors C2 (situation awareness), C3 (communication), C4 (teamwork), C8 (vigilance), and C9 (attention) are under the casual cluster, while C1 (workload), C5 (trust), C6 (fatigue), and C7 (stress) are under the effect cluster. Causal criteria imply that these factors influence the other criteria to some degree. The matrix elements highlighted in grey, as shown in Table 9, indicate significant relations among criteria. Figure 1 also illustrates such a relationship among criteria. It can be noted further that while there are significant relations among pairs of criteria (e.g., C1—C2, C2—C9, C7—C2), there are also insignificant ones (e.g., C6—C8, C9—C4, C8—C5). Such a result implies that one criterion's influence or effect on another can be considered significant or negligible.

To continue the classification of criteria, since causal criteria are those that affect the other criteria, decision-makers are directed towards paying the most attention to such causal criteria in order to improve the overall performance of air traffic controllers. For instance, in reference to the total influential matrix, since C1 (workload) has a significant impact on all the rest of the criteria except C6 (communication), framing an improvement effort specific to C1 (workload) will have a significant impact on other criteria. On the other hand, effect criteria are those that are influenced by causal criteria. For decision-makers, it is also critical to carefully monitor such effect criteria to minimize the impact of other criteria on an effect criterion. As an example, C2 (situation awareness) is influenced by all criteria except C6 (communication); therefore, any strategy formulation efforts are certain to influence C2 (situation awareness). It is very interesting to notice that C6 (fatigue) does not significantly influence other criteria or is influenced by other criteria. This suggests that efforts to improve other criteria will not have a significant impact on C6 (fatigue). As such, dedicated programs specific to handling C6 (fatigue) should be developed by decision-makers.

Classifying the nature of performance-shaping actors as either casual or effect helps decision-makers frame policies with respect to how each factor should be treated to improve the performance of air traffic controllers. However, the fuzzy DEMATEL methodology is limited to only exploring such relationships and the nature of criteria. To aid in the analysis of the criteria, the fuzzy BWM is employed.

Key results of the fuzzy BWM method center on the priority vector of criteria. It is found that among the criteria, C3 (communication) is considered to be the first priority. It is imperative to highlight that decision-makers must carefully look into the priority of criteria in policymaking; for one, it is a given truth that resources, such as time, finances, and labor, available for use in the

improvement programs of the air traffic controllers are limited. Putting most efforts into improving the critical criteria rather than taking everything in one phase can apparently provide improvement to the overall performance of air traffic controllers.

6. Conclusions and Ways Forward

The nature of air traffic controllers' tasks in managing air traffic flow requires maximum performance to ensure that an efficient and safe flow is always observed. The overall performance of air traffic controllers is shaped by a number of factors, such as workload, situation awareness, communication, teamwork, trust, fatigue, stress, vigilance, and attention. While stakeholders in the air traffic management sector strive to enhance the performance of air traffic controllers, no particular guideline is available for decision-makers reference. This paper aims to provide a springboard on which particular factors (or factors) to focus first.

Using fuzzy DEMATEL and fuzzy BWM, these performance-shaping factors are evaluated via a case study performed in the Mactan Control Tower of the Civil Aviation Authority of the Philippines (CAAP) to distinguish the classification of factors and their priority vector. Key results of the model implementation clearly showed the nature of factors being either causal or effect criterion. Furthermore, the priority of each criterion is also known. With such results at hand, it becomes convenient for decision-makers to develop strategies and allocate limited resources to enhance performance by focusing on critical factors. The results showed that there is practically no need for decision-makers to tackle all criteria at once, as addressing one criterion can significantly impact other criteria.

Along the line of the case study performed, the proposed methodology can satisfactorily reflect the decision maker's preference in assessing the factors affecting air traffic controllers' performance under the HPE framework. However, such results should be taken with caution. Although the same interpretation can work for any case study involving the analysis of the same factors, a different classification of factors and their priority weights may be obtained depending on the raw responses of the decision-makers of another case study. Note that this paper serves as a methodological guideline for stakeholders of the aviation industry, in fact, even for other types of industries, to follow in analyzing the interplay among factors affecting the performance of its human capital.

In future work, specific action plans on critical factors can be explored to provide a clearer strategy implementation for decision-makers. Other than that, the priority vector obtained for each criterion can also be used as an input to analytical tools for further evaluation.

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