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Exploring the Impact of Pandemic Measures on Airport Performance

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Abstract: The impact of COVID-19 measures on airport performance is obvious, and there have been numerous studies on this topic. However, most of these studies discuss prevention measures, the effects on airport operations, forecasts of economic impacts, changes in service quality, etc. There is a lack of research on the effects of various prevention measures on airport operations and the interrelationships between these measures. This study focuses on addressing this gap. In this study, an integrated approach is devised that combines the decision-making trial and evaluation laboratory (DEMATEL) method and interpretive structural modeling (ISM). This integrated method is useful for exploring the relationship between pandemic measures and airport performance as well as the complex relationship between them, and the combination of methods improves upon the shortcomings of the original models. This study reveals that mandating vaccination certificates for entry into a country is the most significant measure affecting airport performance. Additionally, aircraft movement at the airport has the greatest overall impact and can be considered the most crucial factor influencing airport performance from an operational standpoint. The findings show that both factors directly influence financial performance, as reflected in the net income. Some management implications are provided to mitigate the consequences of the measures taken to counter the pandemic crisis. This integrated approach should also assist authorities and policy-makers in planning cautious action for future crises.

Keywords: DEMATEL; ISM; MCDM; airport performance; COVID-19 pandemic

Citation: Liou, J.J.H.; Chien, C.W.; Gudiel Pineda, P.J.; Li, C.-S.J.; Hsu, C.-C. Exploring the Impact of Pandemic Measures on Airport Performance. *Aerospace* **2024**, *11*, 373. https://doi.org/10.3390/aerospace11050373

Academic Editor: Álvaro Rodríguez-Sanz

Received: 29 March 2024
Revised: 3 May 2024
Accepted: 7 May 2024
Published: 8 May 2024

1. Introduction

There have been numerous studies related to how international air transportation has been affected by the outbreak of epidemic disease; for example, the outbreaks of H1N1 [1], the Ebola virus [1,2], SARS [3], and MERS [4]. Others have studied the in-flight transmission of communicable diseases such as influenza, measles, smallpox, and tuberculosis [5,6]. However, the COVID-19 pandemic has had an unprecedented effect on air transportation systems and airport operations worldwide, as reflected in their financial statements. Due to the rapid human-to-human transmission and spread of multiple variants of COVID-19, various nations responded by declaring travel bans, closing their borders, and following up with internal lockdowns, limiting any non-essential activities involving human contact, which included traveling [6]. The pandemic has affected every aspect of the air transportation industry, with most of these effects associated with health risks to passengers, crew, airport ground staff, and all stakeholders directly involved, with repercussions spreading to the overall population and the country as a whole. The immediate effect of government-initiated travel and immigration restrictions was a dramatic reduction in demand for air transportation [7]. Currently, according to the latest statistics from the International Air

Transport Association (IATA), in 2023, Revenue Passenger Kilometers (RPK) reached 94.1% of the 2019 levels. In 2023, the aviation industry's RPK reached 94.1% of the 2019 levels. Available Seat Kilometers (ASK) increased by 24.1% year-on-year, recovering to 94.4% of the pre-pandemic levels. The global passenger load factor was 82.3%, slightly below the threshold in 2019. However, the impact of various measures to prevent COVID-19 in the aviation industry on airport operations remains worth exploring.

Measures such as banning the entry of international flights and the requirement that all passengers hold negative PCR tests, as well as other external factors (e.g., the proliferation of new COVID-19 variants and mutations of the virus) and internal factors (e.g., spikes in the number of local COVID-19 cases), have had unavoidable operational and financial impact on airports around the world. According to International Air Transport Association [8] data, there was a 66% decline in demand for world air travel in 2020, as expressed in Revenue Passenger Kilometers (RPKs), compared to the levels of the year before, in 2019. Additionally, the number of flights declined from 38.9 million in 2019 to 16.4 million in 2020; there was a 56.5% decline in the available seat capacity (Available Seat Kilometers) in 2020 [9]. The air cargo sector was also affected by the pandemic [10] but has recovered significantly better than passenger traffic, with only a 0.5% year-on-year decrease in Cargo Ton Kilometers (CTKs) in December 2020 [9]. This is because, with the decline in passenger aircraft movement, passenger aircraft were converted to carry freight as a short- to medium-term strategy for revenue generation [11]. Cargo movement in the absence of passenger movement allowed airlines and airports to remain active and continue receiving some revenue during the pandemic crisis [12]. However, given the nature and severity of the disruptive situation, the financial statements still showed massive losses, with many airlines and airports receiving emergency aid from their respective governments. In the real world, the response to this sort of disturbance requires consultation between governments, airport authorities, airlines operating from the affected airports, and the entities involved in airport operations to discuss their options for changing the original plans to cope with the uncertainties of the situation. However, dependence upon subjective opinions or ambiguous policies and bureaucratic red tape can lead to biases and obstacles in solving the problems related to the operational and financial performance of air transport.

Clearly, managers and decision-makers require a tool specifically tailored to the air industry to help them identify the most influential factors and delineate the complex relationship between these factors, not just to generate an understanding of the issues but to formulate policies and take action that will overcome the damage and mitigate the negative impact of this crisis and possible future events. Multiple-criteria decision-making (MCDM) models are valuable tools for exploring the complex relationship between the factors and identifying the main causal factors. This study aims to provide a tool for instances that require a rapid analytical approach that will allow decision-makers to understand the situation and generate policies to handle emergencies, such as the pandemic situation, that affect airport operations. There have been relatively few studies on the impact of the pandemic on airport operations using MCDM methods. Aurora et al. proposed a method for the assessment of impact and strategies on air transportation systems [6], aviation strategy, a comparison of coronavirus responses, and aviation policies. Shaban et al. applied a duopoly model and quantity discount to manage air cargo disruptions caused by global catastrophes such as COVID-19 [13]. Dabachine et al. utilized parametric modeling and processing algorithms to generate a strategic design for precautionary measures for airport passengers in times of the global health crisis of COVID-19 [14]. Štimaca et al. analyzed the impact of the COVID-19 pandemic on Croatian airports [15], focusing on the level of service and anti-virus measures. Deveci et al. [16] studied the economic impact of COVID-19 on the Turkish civil aviation industry. While there have been many studies on the impact of COVID-19 on airports and the evident effects on airport operations, the literature does not explore which measures are most crucial, nor does it address the relationship between these measures. Therefore, this study aims to fill this gap in the existing literature. The research question we developed is how to assist government departments and management teams in utilizing our research model to quickly identify key influencing factors and propose correct decision-making methods to mitigate the adverse effects of the epidemic crisis.

The proposed model is divided into three stages: (1) finding the relevant factors, criteria, or measures impacting financial and operational performance; (2) exploring the criteria relationship using the decision-making trial and evaluation laboratory (DEMATEL) method and interpretive structural modeling (ISM) method; and (3) mapping and analyzing the causal influential factors (i.e., the network relationship map (NRM) and ISM map) to provide improvement strategies. The proposed model can be used by governmental departments, airport authorities, and management teams in general to facilitate the decision-making process to overcome the adverse effects of the pandemic crisis. This study also contributes to the field of operations research by proposing an integrated approach to analysis based on the MCDM models, which can be applied to explore the relationship between pandemic measures and airport performance to help governments and managers establish an improved policy-making framework.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the related literature. Section 3 describes the proposed analytic MCDM models. Section 4 demonstrates the effectiveness of the MCDM methods by examining the airlines and air traffic industries impacted by pandemic measures over operational and financial factors. Finally, Section 5 presents some conclusions and closing remarks.

2. Literature Review Regarding Airport Performance

Several authors have conducted literature reviews related to airport performance, including those of [17], who presented a collection of papers published between 1997 and 2010 with 59 studies on airport benchmarking; Bezerra et al. [18], who carried out a systematic literature review about performance measurement in airport settings; and Chaouk et al. [19], who published a comprehensive overview of the literature related to performance measurement in airport settings and classified more than 80 related studies that fall into either one of two quantitative approaches: one-dimensional or multi-dimensional. They found that more than 75% of previous studies in the literature had used frontier approaches such as parametric stochastic frontier analysis (SFA), and more than 80% of them had adopted non-parametric data envelopment analysis (DEA).

DEA, a non-parametric approach, has been applied to measure airport performance, followed by a second-stage censored Tobit regression to identify the factors affecting airport efficiency. For example, Graham et al. [20] elaborated a partial performance-measurement framework for examining the economic and financial performance of U.K. airports. They built a model around the derivation of ratios from specific combinations of inputs and outputs. These partial performance frameworks have been applied more extensively in recent studies related to airport management applications. In addition to the traditional DEA models, other researchers have recently proposed network DEA models [21], where airport efficiency is deconstructed into several subsystem efficiencies, which are then used to discuss airport performance. Others have applied DEA to evaluate the physical characteristics, managerial strategies, and governance structures related to airport performance [22]. Chi-Lok and Zhang [23] investigated the influence of competition and aviation policy reform in China on the efficiency of Chinese airports. They estimated both the productivity level and its growth for 25 sample Chinese airports using DEA. They considered runway length and terminal size as the inputs and passengers, cargo, and aircraft movement as the outputs. Güner et al. [24] proposed a weight-restricted network DEA model, which considers network centrality measures as the cornerstone intermediates that establish the link between airport resources and the traffic volume handled. Yu and Rakshit [25] also used the network DEA to analyze the dynamic efficiency and changes in technology gaps of 50 European airports with different ownerships in the period 2011–2017 within the meta-frontier framework.

While most studies have applied DEA to discuss airport performance, other approaches have attempted to assess and address disruptions and issues caused by COVID-19 in the field of air transportation using MCDM or other methods [26,27]. Raghavan and Yu [28] used a regression analysis and proposed a strategy for evaluating financial performance, emphasizing the financial viability and strength of commercial service airports in the United States affected by COVID-19. Guevara and Bonilla [29] developed an algorithmic method that combines fuzzy logic and a Markov chain technique to prevent the spread of COVID-19 in airports and air routes. Additionally, Dimitriou and Sartzetaki [30] developed an ex-ante-assessment-based framework for evaluating the economic effects on the business ecosystem associated with airport operations. Their approach conveyed a key message to national governments, decision-makers, and stakeholders regarding the importance of airport investment for regional economic development, particularly its contribution to the business ecosystem, especially after the COVID-19 pandemic. Tanrıverdi et al. [31] explored the factors affecting airport selection during the COVID-19 pandemic from the perspective of air cargo carriers, aiming for profit optimization. They applied a triangular fuzzy Dombi–Bonferroni BWM methodology. Their study findings reveal that location and costs are the two most important aspects, with airport charges and handling charges being the most crucial factors. Dey Tirtha et al. [32] proposed an airport-level framework for examining the impact of COVID-19 on airline demand. Their framework provided a blueprint for recovering airline demand with the evolution of COVID-19 cases over time. In relation to the optimization of airport consumption, Xue et al. [33] presented a case study of four international airports in China, analyzing the impact of COVID-19 on aircraft usage and fuel consumption based on automatic dependent surveillance-broadcast surveillance data. Gajewicz et al. [34] focused on the criteria for evaluating airport service quality and conducted a statistical analysis of data collected from a diagnostic survey of over 263 passengers at European airports just before the pandemic lockdown. Wu et al. [35] examined the impact of the COVID-19 pandemic on multi-airport systems (MASs) worldwide. Sun et al. [36] applied the data-driven method to examine the patterns underlying market entry decisions during the aviation recovery phase. Hiney et al. [37] explored the impact of the pandemic on airports and Irish airport stakeholder relationships. Furthermore, some authors investigated the effect of COVID-19 on aviation industries from various aspects, such as policies, revenues, or service attributes [38–41].

From the literature review, it can be seen that although many different approaches have been applied in prior studies discussing issues related to the pandemic and its impact, few have used MCDM methods to discuss the impact of pandemic measures on airport performance. There have also been few articles discussing financial and operational factors and the relationship between them specific to the airport industries. This study thus proposes a hybrid method to enable governmental authorities and airport or airline managers to previsualize and thus evaluate the impact of pandemic policy measures before they are made, thus mitigating their possible impacts. The developed MCDM model can be applied as the starting point to achieve a better decision-making process when facing future crises.

It is true that MCDM methods have been applied in the airline industry for problems relating to corporate social responsibility [42], airline strategic management [43], and low-cost carrier problems [44]. Previous studies using the MCDM approach in the air transport industry have relied heavily on the DEMATEL method to construct complex relationships between the criteria [45]. The DEMATEL technique is an analytical method for constructing a structural model to solve complex problems, which relies on an influence relational matrix and related mathematical theories [46]. The proposed DEMATEL method, combined with interpretive structural modeling (ISM), can effectively explore the causal relationship between the factors and elucidate their hierarchical structure, thereby providing decision-makers with useful information for designing strategies for improvement.

3. The Proposed Hybrid MCDM Model

This study proposes a managerial tool for analysis to facilitate decision-making between airport managers, civil aviation entities, and government policy-making entities.

Figure 1 presents a graphical representation of the methods included in the proposed model. The model was constructed with the application of a Delphi survey method to a group of experts in the air transportation industry, coupled with a review of the literature related to airport management aimed at identifying the essential factors or criteria. The experts suggested and selected the relevant criteria, collected data, and elucidated the contextual relationships using the DEMATEL method. The group of experts responded to the DEMATEL survey to provide the data required for this methodological application. Additionally, after the DEMATEL results were obtained, the ISM method was applied to obtain the final cause-and-effect models from both methods for analysis and comparison to obtain the final results and arrive at the conclusions.

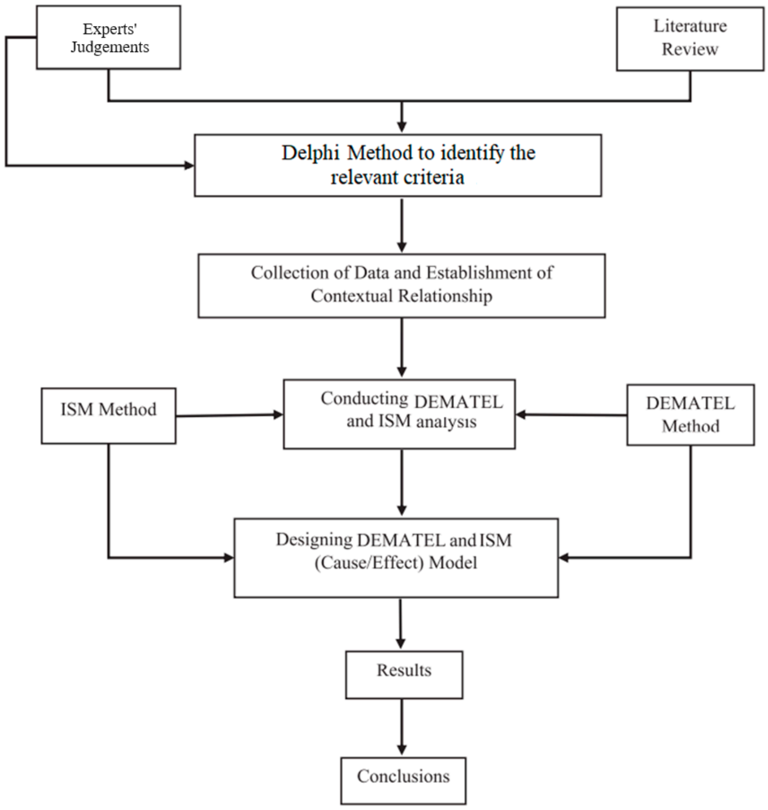

Figure 1. The flow chart of the proposed analysis.

3.1. Delphi Method

The main goal of the Delphi technique is to reach a group consensus from a structured panel of individual experts. It is an efficient process regulated by group-based relationship structures and is used in cases where there is insufficient/indeterminate information. This technique involves going through multiple rounds of surveys where experts may modify their responses until reaching a group consensus [47]. In the classical Delphi method, hesitation, vagueness, and uncertainty may arise since experts express subjective judgments in the form of specific numbers. The application of the fuzzy-Delphi technique, developed by Atanassov in 1983, avoids the aforementioned drawbacks inherent in such a situation. The fuzzy-Delphi technique records experts' opinions in the form of natural language, and analysis occurs through fuzzy sets [48]. Fuzzy numbers, most frequently triangular or trapezoidal fuzzy numbers, are applied in this method to yield valuable results.

In this study, a Delphi survey method was used to arrive at a consensus regarding what the most important pandemic measures to be considered are and which operational and financial factors should be included. In our research survey, we first collected COVID-19 prevention and control measures proposed by various countries. We then invited senior executives from major airports in the Southeast Asian region via email to assess the importance of each measure. Measures considered important by executives, with a rating of over 80%, were retained for the subsequent DEMATEL-ISM investigation stage. The factors relating to pandemic measures were arrived at based on the policies implemented at several major Southeast Asian airports, including Taipei Taoyuan International Airport (TPE), Hong Kong International Airport (HKG), Narita International Airport (NRT), Tokyo International (Haneda) Airport (HND), Incheon International Airport (ICN), Singapore Changi Airport (SIN), Beijing Capital International Airport (PEK), and Pudong International Airport (PVG). The dimension of operational factors was based on data from the Airports Council International (ACI) statistics center, and the dimension of financial factors was based on the annual financial reports for the airports mentioned above. The experts came to a consensus regarding the most important factors for evaluation in the analysis. The Delphi surveys were completed by a panel of air transportation industry experts. After the criteria were determined, the DEMATEL and ISM methods were applied to detect the complex relationships between them and build a relational structure among the relevant factors/criteria.

3.2. DEMATEL Method

The DEMATEL method approach can be used for analysis and decision-making in complex systems. It is micro-oriented and part-based [49]. After obtaining the experts' judgments required to perform the method, the values of influences given or received among the elements under investigation were extracted and presented based on the principles of graph theory. The resulting graphic structural model divides all the factors into cause-and-effect groups [50]. The DEMATEL method shares similarities with the ISM method, but the ISM method cannot determine the intensity of the quantified interactions or the relationships among the factors involved [49]. In this study, we overcome these shortcomings by dividing the analysis into two stages, using the DEMATEL method for analysis in the first stage and applying ISM in the second stage to confirm the presence and the levels of influence. The steps in this method are summarized below.

Step 1: Calculate the initial influence matrix $\boldsymbol{X}$.

Following the identification of important preventive measures through the first-stage Delphi survey, we asked experts to compare the preventive measures generated by the Delphi method pairwise with airports' operational performance to assess their mutual influence levels, thus generating the initial impact matrix $\boldsymbol{X}$. After these scores were obtained, an average matrix of the results could be calculated. The experts' scores serve to establish what degree of influence factor i has on factor j, as indicated by x_{ij}. These results indicate the ranking of influences between elements on an integer scale ranging from 0 to 4, where 0 = an inexistent influence and 4 = an extremely high influence. An average matrix $\boldsymbol{X}$ can be obtained from direct matrices provided by the group of experts' responses, where each element of the average matrix is taken as the mean of the same element given in the responses of each of the experts.

Step 2: Calculate the normalized matrix $\boldsymbol{P}$.

The normalized influence matrix $\boldsymbol{P}$ is derived by normalizing the direct influence matrix $\boldsymbol{X}$. Matrix $\boldsymbol{P}$ reveals the initial effect that each element has on and receives from every other element. The principal goal of using DEMATEL is to create a graphic map of the interrelationship between the elements of a system, wherein the degree of influence is represented by a number (the intensity of influence). The DEMATEL method makes it possible to identify the core causes and effects occurring in a relationship structure and the strength of influence that each factor has over every other criterion.

The full direct/indirect influence matrix is needed to conduct a continuous reduction in the indirect effects of the problems of the powers of matrix $\boldsymbol{P}$, e.g., $\boldsymbol{P}^1, \boldsymbol{P}^2, \boldsymbol{P}^3, \ldots, \boldsymbol{P}^\infty$, so that it will ensure convergent solutions to the matrix inversion. By applying this analytical method, we can display an infinite series of direct and indirect effects.

Matrix $\boldsymbol{P}$ can be calculated by

$$\boldsymbol{P} = z.\boldsymbol{X},\ r > 0, \tag{1}$$

where

$$z = min\left[\frac{1}{max_{1\leq i\leq n}\sum_{j=1}^{n}|x_{ij}|}, \frac{1}{max_{1\leq i\leq n}\sum_{i=1}^{n}|x_{ij}|}\right]; \tag{2}$$

$$\lim_{m\to\infty}\boldsymbol{P}^m = [0]_{n\times n},\ \boldsymbol{P} = \left[p_{ij}\right]_{n\times n},\ \text{and } 0 \leq p_{ij} < 1.$$

Step 3: Calculate the total-influence matrix $\boldsymbol{B}$*.*

The total-influence matrix $\boldsymbol{B}$ can be obtained by

$$\boldsymbol{B} = \boldsymbol{P} + \boldsymbol{P}^2 + \boldsymbol{P}^3 + \cdots + \boldsymbol{P}^m = \boldsymbol{P}(\boldsymbol{I} - \boldsymbol{P})^{-1},\ \text{when } m \to \infty. \tag{3}$$

In Equations (4) and (5), the rows and columns are summed by placing vectors $\boldsymbol{r}$ and $\boldsymbol{c}$, respectively, within the total-influence matrix $\boldsymbol{B}$.

$$\boldsymbol{B} = \left[b_{ij}\right];\ i,j = 1,2,\ldots,n;$$

$$\boldsymbol{r} = [r_i]_{n\times 1} = \left(\sum_{j=1}^{n} b_{ij}\right)_{n\times 1}; \tag{4}$$

$$\boldsymbol{c} = [c_i]'_{1\times n} = \left(\sum_{i=1}^{n} b_{ij}\right)'_{1\times n}. \tag{5}$$

In Equation (5), the superscript $'$ indicates transposition.

Suppose that r_i indicates the row sum of the ith row matrix $\boldsymbol{B}$; then, r_i shows the sum of the direct and indirect effects of factor i on the other factors/criteria. If c_i denotes the column sum of the jth column of matrix $\boldsymbol{B}$, then c_i shows the sum of direct and indirect effects that factor i has received from the other factors. Moreover, when $i = j$ (i.e., the sum of the row and column aggregates), $(r_i + c_i)$ provides an index of the intensity of influences given and received; that is, $(r_i + c_i)$ gives the degree that factor i poses in the problem. If $(r_i - c_i)$ is positive, then factor i affects the other factors, and if $(r_i - c_i)$ is negative, then factor i is influenced by the other factors [51].

Step 4: Obtain the IRM.

Each element b_{ij} of matrix $\boldsymbol{B}$ gives information about how element i influences element j. The network relationship map (NRM) can be constructed by detecting and selecting elements from matrix $\boldsymbol{B}$. The threshold value is identified from expert opinions (e.g., obtained by group creativity techniques such as brainstorming) and by deriving the average of the matrix $\boldsymbol{B}$ after the threshold value and relative NRM are established. The final results of the application of the DEMATEL method are illustrated as an NRM.

3.3. Interpretive Structural Modeling

The ISM method can use qualitative data to transform a complex structure into multiple alternatives based on expert opinions, which simplifies the creation of a structural model [52]. The ISM is frequently applied in management problems that involve complex structures and multiple criteria. The problem's structure is divided into subcategories, and the aim of the method is to identify and summarize the relation among the elements based on the levels [53]. The steps for the application of the ISM method are as follows:

Step 1: Generate the SSIM from the results of the DEMATEL analysis

Formulate the Structural Self-Interaction Matrix (SSIM) based on the DEMATEL method. In this study, the SSIM was derived from the total influence matrix produced by DEMATEL. For each element (i, j) of the SSIM, if the degree of influence of i on j is greater than the average of the total influential degree, then (i, j) is assigned a value of 1; otherwise, it is 0.

$$\begin{cases} k_{ij} = 1, b_{ij} > \delta \\ k_{ij} = 0, b_{ij} \leq \delta \end{cases} \tag{6}$$

where δ is the average of total influential degree.

Step 2: Calculate the reachability matrix from the SSIM

Conduct a transitivity check of the reachability matrix by applying the rules of transitivity, which gives a matrix model that has thus been developed to derive the final reachability matrix. The transitivity principle establishes that if "Factor-W" affects "Factor-X" and "Factor-X" affects "Factor-Y", then "Factor-W" affects "Factor-Y".

Step 3: Determine the reachable set R_i and antecedent set A_i

$$R_i = \{\alpha_j | \alpha_j \in X, k_{ij} \neq 0\} \tag{7}$$

$$A_i = \{\alpha_j | \alpha_j \in X, k_{ji} \neq 0\} \tag{8}$$

Check whether Equation (9) holds. If it does, it indicates that the factor i is a fundamental factor, and should be deleted from the i-th row and column in reachability matrix.

$$R_i = R_i \cap X_i \tag{9}$$

Step 4: Divide the factors into different levels

Rank the factors by splitting them into different levels based on the final reachability matrix, applying the reachability and antecedent sets. The reachability set requires the assembly of criteria that contain the inner and external influence of each criterion, whereas the antecedent set is integrated from the criteria that affect itself and the other criteria.

Step 5: Plot the factors as hierarchical levels

Compute the canonical matrix by classifying the criteria into different levels to establish their driving and dependence power along the rows and columns obtained by assembling the antecedent and reachability sets. Repeat steps three and four to ensure that all factors i are removed. Plot the digraph based on the SSIM and reachability matrix and rank them accordingly; then, proceed to obtain the final structural ISM from the digraph.

4. Investigation and Analysis

In the empirical example, we selected experts with knowledge related to airport operations, flight operations administration, financial management, and civil aviation procedures who had also been involved in decision-making for COVID-19 pandemic measures to mitigate operational and financial disturbances in the past few years. These experts had professional experience and understood all of the airports' operational and financial factors, as well as being familiar with international airport standards and government regulations. According to the research by Rezaei et al. [54] and Quayson et al. [55], expert opinion surveys of this kind require experts with sound knowledge regarding the entire system's operation and a clear grasp of the survey methodology. Therefore, obtaining credible results typically requires only 4–15 experts. The entire survey was conducted from April to November 2021. Due to some experts holding official positions and preferring not to be identified, the survey was conducted anonymously. The seven experts involved in this study included operation control center employees, airport management employees, and airline station managers and supervisors (including airline operations controllers and dispatchers) from different airports. They included civil aviation authorities and airline customer service coordinators and worked for different airlines and institutions (e.g., General Directorate of Civil Aeronautics of Guatemala, Civil Aeronautics Administration (Taiwan), United Airlines, American Airlines, Delta Airlines, and Emirates Airlines). In this study, the main criteria were derived from ACI statistics.

The experts were asked to complete surveys based on the Delphi method, from which we obtained a set of well-defined criteria (factors) related to the impact of pandemic measures on operational and financial factors. The Delphi method also enabled the experts to suggest additional criteria. Finally, the experts were able to obtain a consensus. The final list of criteria appears in Table 1.

Table 1. Factors affecting airport performance and pandemic measures.

Goal	Dimensions	Criteria/Factors
Establish performance improvement planning goals for airport performance to overcome the pandemic crisis	(D_1) COVID-19 measures	(C_{11}) PCR COVID-19 testing required to enter the country (C_{12}) Vaccination Certification required to enter the country (C_{13}) Ban restriction of entry for specific countries (C_{14}) Amount of COVID-19 cases imported to the country (C_{15}) Amount of domestic COVID-19 cases within the country
	(D_2) Operational Factors	(C_{21}) Passenger movements in the airport (C_{22}) Cargo movement in the airport (C_{23}) Aircraft movement in the airport
	(D_3) Financial Factors	(C_{31}) Net income (C_{32}) Operating profit (C_{33}) Operating revenue (C_{34}) Operating expenses

4.1. Measuring the Relationship between Criteria and Dimensions

After the criteria were defined, the DEMATEL method was applied to determine whether the criteria exhibit an interrelationship (influence degree) and the direction of this interrelationship. On the basis of the DEMATEL method, the experts determined the influential levels of the criteria. These data determined the content of matrix $\boldsymbol{X}$, which was established by calculating the mean obtained from the DEMATEL survey. The average initial direct-relation 12×12 matrix $\boldsymbol{X}$, obtained using the pairwise comparisons of influences and directions between criteria, is shown in Table 2.

Table 2. Initial influence matrix.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{34}
C_{11}	0.000	0.429	3.000	3.714	3.327	3.714	0.286	3.429	2.857	3.429	2.571	3.714
C_{12}	1.429	0.000	3.286	2.857	3.000	1.429	0.143	1.000	0.857	1.286	2.000	0.429
C_{13}	2.857	3.429	0.000	4.000	1.714	3.857	0.571	2.714	3.571	3.143	2.857	3.429
C_{14}	3.857	3.429	2.286	0.000	3.714	1.857	0.286	1.286	1.714	1.571	1.143	1.857
C_{15}	3.571	3.714	2.857	0.286	0.000	2.857	0.143	1.143	2.286	2.000	2.143	3.571
C_{21}	0.286	0.000	0.143	0.286	0.571	0.000	0.429	3.429	3.429	2.571	2.286	3.286
C_{22}	0.000	0.143	0.429	0.286	0.143	0.429	0.000	3.714	3.714	3.286	3.000	2.429
C_{23}	0.857	0.143	0.286	2.429	2.286	4.000	4.000	0.000	3.714	3.857	3.571	3.857
C_{31}	0.000	0.000	0.000	0.000	0.000	1.000	0.714	0.857	0.000	0.000	0.000	0.000
C_{32}	0.000	0.000	0.000	0.000	0.000	0.429	0.286	0.143	4.000	0.000	2.000	0.286
C_{33}	0.000	0.000	0.000	0.000	0.000	1.286	1.714	1.714	4.000	4.000	0.000	1.286
C_{34}	0.000	0.000	0.000	0.000	0.000	2.429	2.143	1.571	4.000	4.000	3.286	0.000

The normalized direct relation can be calculated by applying Equations (1) and (2). After the calculation is carried out, the total influence matrix can be derived by using Equation (3), as shown in Table 3. The sums of the influences given and received by each dimension are calculated using Equations (4) and (5) (see Table 4). The network relationship map (NRM) is plotted from the total influence matrix (Table 3), as illustrated in Figure 2. Furthermore, Table 5 gives the sums of influences given and received by the dimensions; we also provide the NRM mapping of the relations between the dimensions (see Figure 3).

Table 3. Total influence matrix.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{34}
C_{11}	0.051	0.058	0.123	0.150	0.146	0.204	0.065	0.180	0.237	0.221	0.178	0.204
C_{12}	0.084	0.040	0.128	0.120	0.127	0.110	0.035	0.086	0.124	0.118	0.124	0.083
C_{13}	0.129	0.136	0.048	0.163	0.110	0.207	0.071	0.164	0.255	0.214	0.186	0.194
C_{14}	0.154	0.137	0.112	0.052	0.157	0.140	0.047	0.110	0.170	0.147	0.121	0.139
C_{15}	0.136	0.134	0.119	0.058	0.047	0.164	0.047	0.107	0.191	0.161	0.149	0.179
C_{21}	0.019	0.008	0.013	0.023	0.032	0.044	0.048	0.132	0.176	0.134	0.114	0.132
C_{22}	0.011	0.012	0.020	0.024	0.020	0.056	0.037	0.140	0.186	0.154	0.134	0.108
C_{23}	0.053	0.029	0.033	0.092	0.095	0.181	0.158	0.076	0.240	0.213	0.186	0.183
C_{31}	0.002	0.001	0.002	0.003	0.004	0.036	0.027	0.034	0.015	0.012	0.011	0.011
C_{32}	0.001	0.001	0.001	0.002	0.002	0.023	0.018	0.016	0.135	0.015	0.066	0.017
C_{33}	0.005	0.003	0.004	0.008	0.008	0.062	0.070	0.075	0.170	0.150	0.034	0.062
C_{34}	0.005	0.003	0.004	0.009	0.009	0.099	0.088	0.081	0.186	0.164	0.134	0.034

Table 4. Sum of influences given and received on criteria.

Criterion	r	c	$r + c$	$r - c$
C_{11}	1.818	0.651	2.468	1.167
C_{12}	1.180	0.561	1.741	0.619
C_{13}	1.878	0.606	2.484	1.272
C_{14}	1.486	0.703	2.190	0.783
C_{15}	1.491	0.757	2.248	0.733
C_{21}	0.876	1.328	2.205	−0.452
C_{22}	0.901	0.713	1.614	0.189
C_{23}	1.541	1.201	2.742	0.339
C_{31}	0.159	2.085	2.244	−1.927
C_{32}	0.298	1.703	2.001	−1.405
C_{33}	0.650	1.438	2.088	−0.788
C_{34}	0.816	1.346	2.162	−0.530

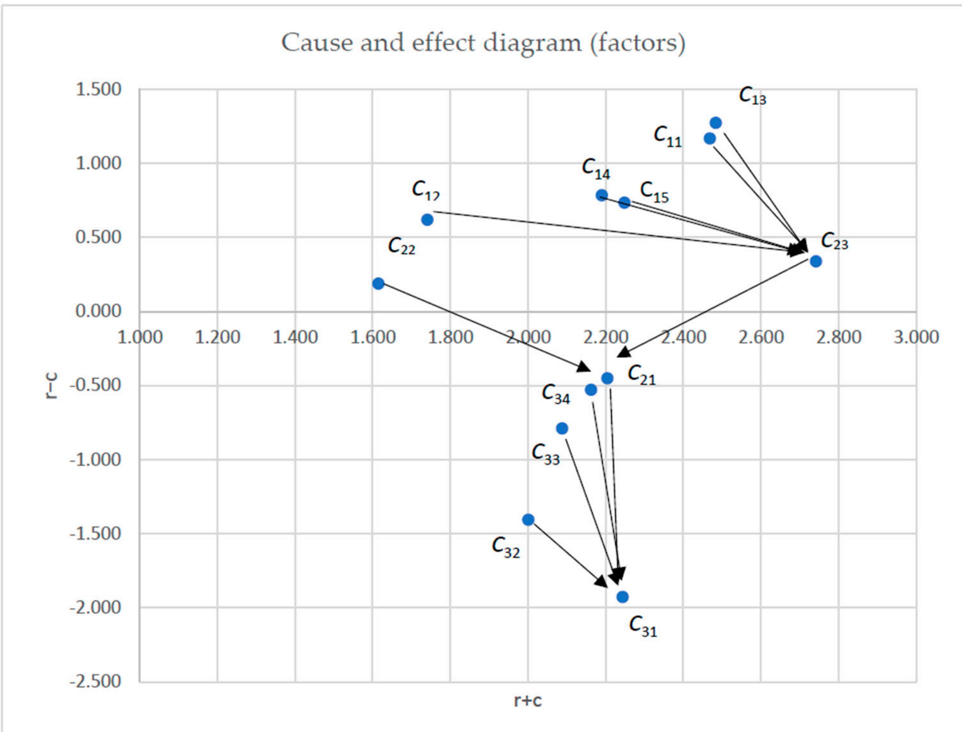

Figure 2. Network relation map (NRM) between criteria.

Table 5. Sum of influences given and received on dimensions.

	r	c	$r+c$	$r-c$
COVID-19 factors (D_1)	0.394	0.145	0.539	0.250
Operational factors (D_2)	0.293	0.265	0.558	0.027
Financial factors (D_3)	0.132	0.409	0.542	−0.277

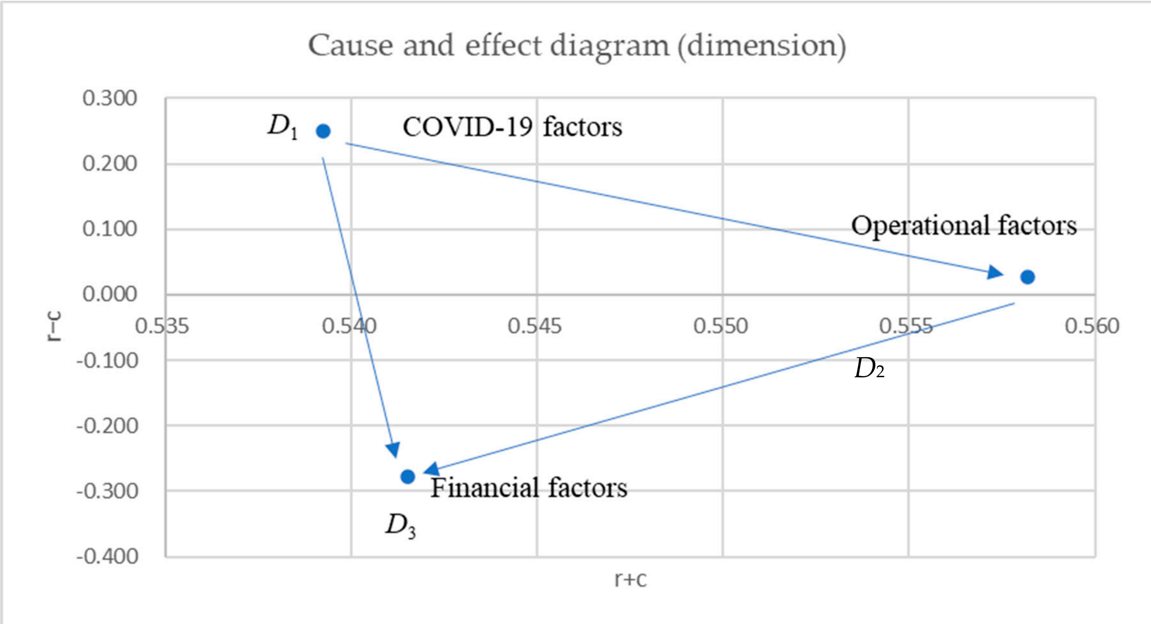

Figure 3. Network relationship map (NRM) between dimensions.

The NRM provides a graphic representation of the direction of influence between the dimensions and the criteria. In the NRM appearing in Figure 3, the pandemic measure dimension (D_1) is marked with an arrow pointing to the operational criteria dimension (D_2), both of which point to the financial criteria dimension (D_3), indicating how external criteria, such as pandemic factors (uncontrollable factors in managerial terms), directly affect the internal operational criteria (controllable factors as the operational and financial dimensions). The network relationships within dimension (D_1) indicate that all the criteria directly or indirectly affect the net income (C_{31}), which is thus displayed in the very lowest part of the graph. These results reveal how all actions or influential factors related to the pandemic and changes affect airports economically.

4.2. Using ISM to Obtain the Hierarchical Structure of the Factors

Based on the total influence matrix (Table 3), we proceed to integrate the reachability matrix by converting the resulting numbers. If the elements of the total influence matrix have an average value less than the total matrix value, then they are assigned a value of 0; if the value is greater than the average, then they are assigned a value of 1. The reachability matrix can be obtained, as shown in Table 6.

This is followed by the iterations for level partitioning in ISM. These are guided to plot the final levels graph, and the iterations are performed for the partitions of different levels for the criteria contained in each dimension. Based on the iteration level, the final hierarchy levels between the criteria are obtained, as shown in Figure 4.

Table 6. Final reachability matrix.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{34}
C_{11}	1	0	1	1	1	1	0	1	1	1	1	1
C_{12}	0	1	1	1	1	1	0	0	1	1	1	0
C_{13}	1	1	1	1	1	1	0	1	1	1	1	1
C_{14}	1	1	1	1	1	1	0	1	1	1	1	1
C_{15}	1	1	1	0	1	1	0	1	1	1	1	1
C_{21}	0	0	0	0	0	1	0	1	1	1	1	1
C_{22}	0	0	0	0	0	0	1	1	1	1	1	1
C_{23}	0	0	0	1	1	1	1	1	1	1	1	1
C_{31}	0	0	0	0	0	0	0	0	1	0	0	0
C_{32}	0	0	0	0	0	0	0	0	1	1	0	0
C_{33}	0	0	0	0	0	0	0	0	1	1	1	0
C_{34}	0	0	0	0	0	1	0	0	1	1	1	1

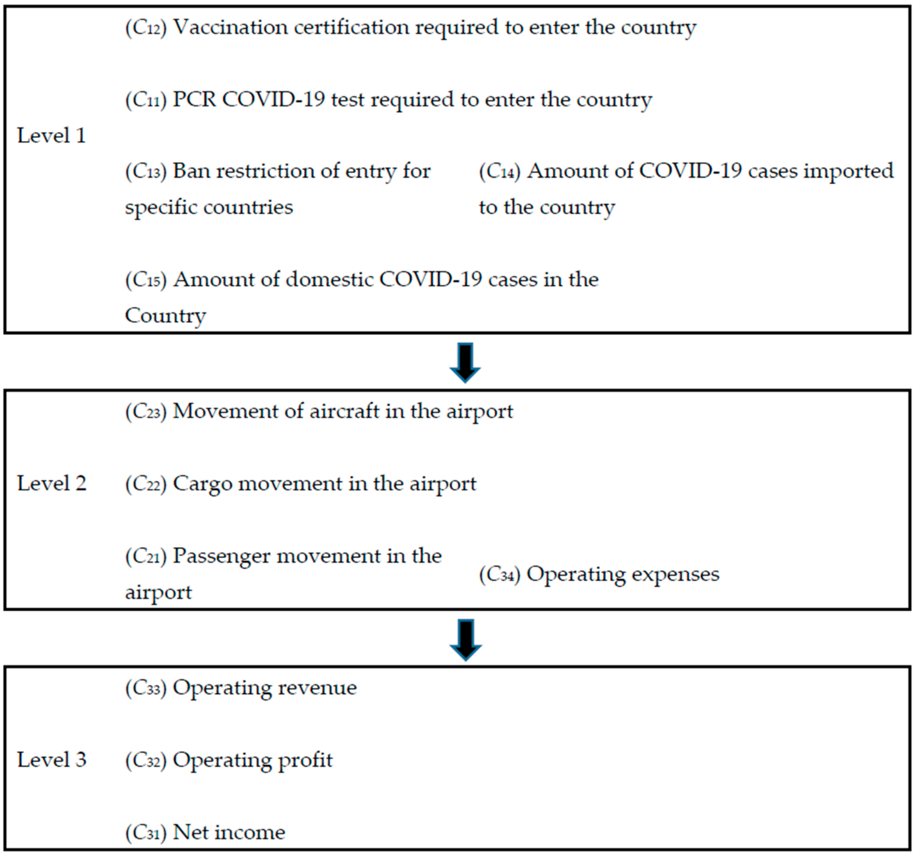

Figure 4. ISM graphic representation of the levels of influence between criteria.

5. Results and Discussion

The ISM results indicate the presence of influence factors among all the other dimensions. Level 1 includes the requirement of a PCR test to enter the country (C_{11}), a vaccination certification required to enter the country (C_{12}), bans and restrictions to entry for specific countries (C_{13}), the number of COVID-19 cases imported to the country (C_{14}), and the number of domestic COVID-19 cases in the country (C_{15}). These are the most critical measures that impact airport performance. Aircraft movement in the airport (C_{23}) had the largest total influence degree, so it is viewed as the most essential factor for airport performance. The aforementioned factors had a direct impact on the financial performance. An increase in operating expenses had an overall effect on the final net income. Increased losses prevailed for a long period of time during the pandemic crisis. The findings show that both factors directly influenced the financial performance of the airport, as reflected in the net income. Some management implications are provided in the discussion to mitigate the negative impact of the pandemic crisis.

Important management implications can be derived from the preceding DEMATEL analysis and by examining the influence on the dimensions and the criteria (Tables 4 and 5). From the results, we found that the dimension of COVID-19 (D_1) had a higher influence than other operational factors, with a positive ($r - c$) value of 0.250 compared to a value of (0.027) for (D_2). This indicates that the airport authorities should consider COVID-19 factors (D_1) as having a higher priority when evaluating the impact of pandemic measures on the airport ecosystem. In terms of criteria related to airport operations (D_2), the results of ISM and DEMATEL combined show that the "movement of aircraft in the airport" (C_{23}) had the highest impact, greater than "cargo movement in the airport" (C_{22}) or "passenger movement in the airport" (C_{21}). All are in the same dimension, and all are affected by the COVID-19 factors (D_2), whereas "Net income" (C_{31}) had a negligible effect on establishing measures to overcome the problems caused by the pandemic crisis.

According to the DEMATEL results, the COVID-19 factors (D_1), and operational factors (D_2) directly impacted the financial dimension (D_3), which was deemed an essential factor because it directly influenced all the other criteria and airport performance. In other words, the results reveal that every decision affected the airports' overall net income. This result is also represented in the NRM, as shown in Figure 2, where dimension (D_3) appeared in the lower part of graph $C_{31,}$ indicating that it was influenced by all the other criteria, having the largest ($r + c$) value. In addition, the graph reveals that the criterion (C_{13}), "ban restriction of entry for specific countries", was on level one of the ISM results. It also had the highest net influence ($r - c$) value of 1.272 (see Table 4). Therefore, authorities should avoid using this measure to counter pandemic problems because it will have such a significant impact on airport performance. Furthermore, the criteria on ISM level one (Figure 4) were the root causes of disruption of airport performance. Observing the NRM (Figure 3), we found that the COVID-19 dimension (D_1) influenced the operations dimension (D_2). However, the COVID-19 factors were subject to uncertainty (e.g., the arrival of new sub-variants of the virus or the emergence of new epidemic diseases), which suggests that internal airport operations should be adjusted on the basis of external conditions. Therefore, airport managers and policy-makers should consider external conditions before selecting pandemic measures that might impact overall airport performance.

Airport managers and policy-makers can refer to the results obtained from this hybrid model approach to make better, more informed decisions. The proposed model provides an efficient method for evaluating the most appropriate pandemic measures and the impact of the process because it reflects the consensus of experienced airport managers from five different airports (in the U.S., Guatemala, Aruba, Egypt, and Taiwan). Unlike previous approaches, this hybrid model considers all the factors involved (criteria) in terms of priorities (impact and interrelationship). The application of the model to the current case clarifies the main criteria and their impact levels. The calculations are performed to minimize the negative consequences of the selection of future measures related to pandemic crises. Both financial costs and airport operation measures need to be established based on performance improvement planning goals to overcome a crisis such as the presented pandemic case.

This practical and flexible tool can help airport managers focus on performance improvement planning goals for airport performance issues while maintaining control over operational costs and the impact of financial factors. It can help airports remain competitive and also lead to improved safety during a crisis. The results show that the proposed model is suitable for making decisions in a disruptive situation. In addition, this study demonstrates how this combination of the DEMATEL and ISM methods can provide air transportation professionals with a means of measuring the influence and interrelationships of the relevant criteria. In short, this hybrid method enables individuals and companies to make multi-criteria decisions in a timely and cost-efficient manner, different from previous studies using complex programming models. Companies can easily change the parameters used in the proposed model to suit their own needs and make efficient performance improvement planning goals to determine airport performance in future situations caused by other types of disturbances.

6. Conclusions

In this study, the Delphi method was used to identify the criteria that would affect airport performance. The criteria were derived by a group of experts composed of airport managers and other managerial authorities. The expert consensus yielded twelve criteria and three dimension factors. Following the proposed procedures, the DEMATEL method was applied to discover existing interrelationships among the criteria. This method, when used in conjunction with the ISM, enabled us to confirm the presence of interrelationships and synthesize and express priorities as levels of influence. Our results indicate that factors and conditions related to COVID-19 do indeed affect airport operations and financial performance. Regarding COVID-19 factors, we found that restrictions banning entry from specific countries (C_{13}) were a causal factor (net influence = 1.272) and that the net income was the affected factor (C_{31}) (net influence = -1.927). Aircraft movement (C_{23}) had the largest total influence, with a total degree of influence equal to 2.742. Additionally, the ISM results indicate that the requirement of a vaccination certification to enter the country is the most critical measure but less harmful to airport performance, while the movement of aircraft in the airport has the largest total degree of influence, so it can be viewed as the essential factor for airport performance. The findings show that both factors directly influenced the financial performance of the airport as reflected in their net income. Managers should select emergency pandemic measures and policies that satisfy the requirements of national security but consider airport operational conditions and prioritize feasible alternatives according to other criteria. In summary, this study provides a new systematic approach that can be used to solve decision-making problems related to airport performance impacted by pandemic measures over operational and financial factors. In this study, it was found that restrictions banning entry from specific countries are the measures with the highest degree of net influence, as they significantly impact airport revenues. Therefore, in the event of a similar emergency situation like COVID-19 in the future, authorities should avoid implementing this measure to prevent airports from facing operational challenges.

Although the present study contributes to the literature related to the air transportation industry, it does have some limitations. The data collected in this study were converted into set values. However, these values may be uncertain because of incomplete information provided by the experts. Furthermore, inherent conflicts between various departments and differences in expertise levels among the study participants may have skewed these results. By using other analytical methods, such as a complementary DANP, BWM, fuzzy numbers, or gray theory, researchers can re-examine and expand on our findings.

Author Contributions: C.W.C.: Writing—review and editing. J.J.H.L.: Conceptualization and supervision. P.J.G.P.: Writing—original draft, C.-S.J.L.: Writing Literature Review and discussion section. C.-C.H.: Formal analysis, methodology. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data contained within article.

Conflicts 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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