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The performance of major airports in the Europe, NorthAmerica and Asia

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Abstract

Purpose - This study aims to provide a meaningful comparison of airports' performance and better understand the differences observed in the analysed airport performance by presenting a model to analyse the relationship between operational and financial performance and airport characteristics.

Design/methodology/approach - This study uses a quantitative analysis approach. TOPSIS and entropy weight were utilised to analyse 17 airports in three Airports Council International regions: Asia, Europe and North America. Through operational and financial factors, these sample airports identified the most efficiently operated airports from 2016 to 2019.

Finding - Overall, Asian airports were superior in operational and financial efficiency. Unlike operating performance, the sample airport's financial and total performance results show a similar trend. There were no noticeable changes in operational factors. Therefore, differences in financial variables for each airport may affect the total performance.

Practical implications - This study provides insightful implications for airport policymakers to establish a standardised information disclosure foundation for consistent analysis and encourage airports to provide this information.

Originality/value - The adoption of EBITDA to debt ratio and EBITDA per passenger, which had previously been underutilised in the previous study as financial factors, demonstrated differences between airports for airport stakeholders. In addition, the study presented a model that facilitates producing more intuitive results using TOPSIS, which was relatively underutilised compared to other methodologies such as DEA.

Keywords: Airport management, Airport efficiency performance, TOPSIS, Operational and Financial performance

1. Introduction

Air transportation is an essential connection between goods and people between many countries and their members worldwide (Gibbons and Wu, 2020). This connectivity enables helpful support for humanitarian logistics compared to sea transportation. Since most emergency relief supplies are delivered through air charter flights, infrastructure such as airports is an essential factor for rapid response. They must also have adequate capabilities to handle large aircraft, e.g., Boeing 747. (Roh et al., 2015). The economy's rapid growth and rising cargo demand generate a new pressure environment that should not be disregarded as airport management efficiency improves (Bottasso et al., 2013; Mayer, 2016). All airports operate with fast connectivity of passengers, mail and air freight to individual countries as hubs for airlines. Efficient airports develop air freight demand, and the global supply chain utilising this connection will be the key to future competitive advantage (Alkaabi and Debbage, 2011; Rezaei et al., 2017). Hence, the importance and demand for air freights and airports continues to rapidly increase (Airbus, 2019; Boeing, 2020; World Bank, 2021).

As the air freight industry has shown remarkable growth in the global economy, air connection has become a crucial part of the national economy in the transportation of high value-added cargo. Following this increasing trend of connectivity, it has become a significant challenge to consider air connections between these airports (Boonekamp and Burghouwt, 2017; Walcott and Fan, 2017). Generally, measuring and comparing airport performance is a challenging business, due to the various control factors that must be considered. For instance, high levels of quality differentiation, different ownership, regulatory structures, different service mix, operational characteristics, and external constraints like location and environmental factors (Oum et al., 2003; Iyer and Jain, 2019). Nevertheless, the performance of airports has been the main subject of review by many researchers (Barros and Dieke, 2008; Lam et al., 2009; Lai et al., 2012; Fasone and Zapata-Aguirre, 2016; Pacagnella et al., 2021). They argued that airport efficiency analysis is a crucial part of airport management.

However, we discovered several study gaps. Date Envelopment Analysis (DEA) has been used to quantify airport efficiency in several studies that have concentrated on the performance of airports in one country (Gibbons and Wu, 2020). Moreover, as these studies utilizing DEA set the identified variables to input and output, they were not individually analyzed, such as the operational and financial aspects of the airport (Barros and Dieke, 2008; Iyer and Jain, 2019; Lai et al., 2015; Lam et al., 2009; Wang and Song, 2020). Finally, several studies analyzed financial performance (Lai et al., 2015; Sarkis and Talluri, 2004; Tsui et al., 2014; Yang, 2010). However, they adopted total or operating revenue as a measurement variable. Although total revenue covers both aeronautical and non-aeronautical revenue generated at the airport (Lai et al., 2015), the financial performance of the airport should be evaluated using various financial and commercial performance indicators, including airport charges, airport financial strength, sustainability, and the performance of individual commercial functions (ACI, 2012). Therefore, additional analysis of operational and financial performance is required. A detailed analysis of financial performance related to aeronautical, non-aeronautical, and commercial revenue is needed, including operating revenue.

Given the above, three essential research questions emerge. First, which airports are considered to operate efficiently in terms of international and hub airports? Second, will there be differences in airports' performance based on sector-specific analysis? Finally, what are the differences between variables and methodologies utilised in previous studies and other variables and methodologies? To answer these questions, the objective of this study is to examine using a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)-based methodology with international airports and hub airports in three Airports Council International (ACI) regions (Asia, Europe and North America).

This study aims to provide a meaningful comparison of airports' performance and better understand the differences observed in the analysed airport performance by presenting a model to analyse the relationship between operational and financial performance and airport characteristics using TOPSIS. We analyse airports' operational and financial performance nationally and rank them.

The remainder of this paper consists of the following. Section 2 reviews several studies measuring the performance of airports. In Section 3, the TOPSIS approach is conceptualised, and a description of the secondary data is performed. In Section 4, TOPSIS analysis is performed and the findings are discussed. Section 5 concludes the (Tsui, Balli, Gilbey, & Gow, 2014) main findings of the study.

2. Literature Review

2.1. Measuring the airport performance

Airport operators and other airport industry-related organisations continue to recognise airport performance evaluation and benchmarking using it. It identifies best practices for airport operations and enables management to help improve airport performance. For investors and banks interested in privatising airports, benchmarking techniques are used to identify business opportunities, while regulators and airports also utilise benchmarking in their policies to set user rates (Baltazar et al., 2018) However, airport decision-makers encounter complex decision-making challenges related to airport planning, design and operation. This process is complicated for them because many stakeholders in the process may have conflicting objectives for airport performance evaluations (Zografos and Madas, 2006). Many scholarly contributions have been made to support this phenomenon by introducing diverse methodologies. They include Multi-criteria decision analysis (MCDA), including DEA, TOPSIS and MACBETH, and regression analysis. However, no specific methods facilitate measuring and comparing airport performance based on methodical methods within the airport industry (Oum et al., 2003).

2.1.1. The studies on total airport performance

As DEA is a non-parametric technique for fitting a frontier based on best practices using linear programming, it has been utilised in several studies to assess the efficiency of airports around the world (Fragoudaki and Giokas, 2016). The efficiency associated with the operation of airports is obtained through airports, airlines, passengers, air traffic control and firefighting services. They are measured by labour, terminal facilities, aviation facilities, such as runways, and total and non-aeronautical revenues (Wang et al., 2004).

As the movement of goods and passengers between countries increases, the number of aircraft movements, passengers and cargoes becomes the most crucial factor in the airport due to its essential nature that provides contact points between aircraft and passengers or cargo (Fragoudaki and Giokas, 2016; Iyer and Jain, 2019; Lam et al., 2009). Therefore, the number of passengers, aircraft, and cargo movements are critical indicators of airport performance and efficiency (Baltazar and Silva, 2020). In addition to these variables, runways and terminals were also utilized as variables to measure airport performance. Several researchers have utilised infrastructure-related variables (Chae and Kim, 2015; Lai et al., 2015; Wang and Song, 2020; Pacagnella et al., 2021) as they represent the number and size of aircraft that the airport enables it to handle. According to Fragoudaki and Giokas (2016), runway length is a rudimentary infrastructure, and it is possible to predict the size of an aircraft that can take off and land at each airport. They argued that the size of the terminal might indicate the ability of the airport to handle passenger flow at a certain level. The number of runways, terminal area size, and runway length reflects the capacity of airports.

On the other hand, several studies employ regression analysis to investigate the relationship between variables affecting airports. According to Oum et al. (2003), the number of people and cargo movements impacts the airport's landside operating profit, whereas aircraft and cargo movements affect the airport's airside operating profit. Fasone et al. (2016) suggested that non-aeronautical activities have a significant impact on the commercial revenue of the airport. They insist that retail space, flight distance, international gateway, aircraft movement, and the number of passengers affect airport performance and that non-core activities should also be concerned with revenue from improvements. These studies focused on the productivity and financial capabilities of the airport. They verified their impact by using variables related to the efficiency of the airport as inputs (independent variables) and outputs (dependent variables). Although these studies employed regression analysis, they are not studies of which airports operate most efficiently. The variables adopted by the authors is worth using to derive variables in the future because they presented results that affect airport productivity and financial performance.

2.1.2. The studies on airport financial performance

The aforementioned studies are studies that simultaneously analysed operating and financial factors, but there are also studies dealing with airports' efficiency using financial factors. Humphreys and Francis (2002) considered the past, present and future of airport performance measurements and discussed the changing processes. They provide traffic income per Work Load Unit (WLU), commercial income per passenger, concession income per passenger and duty- and tax-free income per international departing passenger as factors to measure their financial performance. These factors go beyond the existing WLU in the analysis of the financial performance of the airport. The authors argued that although methods have been developed to analyse current airport performance measures, various analytical information for benchmarking should be developed. Barros and Dieke (2008) also insisted that WLU parameters are also factors that increase efficiency. Total cost, operating cost and WLU should be dealt with in terms of productivity and cost effectiveness. Data from economic reports or financial accounts are critical for assessing financial performance. (Baltazar and Silva, 2020).

For the total revenue from the output, Lai et al. (2015) demonstrated that it was appropriate because the importance of non-aeronautical revenue was increasing. However, studies using commercial profits as outputs have been limited due to the difficulty of obtaining financial information on commercial profits at airports (Iyer and Jain, 2019). Although non-aeronautical revenue had a significant positive impact on the operational and financial efficiency of the airport (Chae and Kim, 2015), previous studies ignored the impact of commercial services on airport efficiency, employing input and output variables related to aviation services instead (Wang and Song, 2020). The non-aeronautical revenue contributes significantly to the profitability and sustainability of major airports in the world. Therefore, operating profit, net profit, aeronautical revenue, and non-aeronautical revenue are essential in measuring airport efficiency (Ha and Moon, 2015). Furthermore, financial performance was stated as an examination of operational expenses, spending evolution, revenue evolution, investment, debt, Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA), cash flow, profit/loss, operating margin, profitability ratios (ROA, ROE, ROI), and internal rate of return (Bezerra and Gomes, 2018). Ha and Moon (2015) argued that if analysis using a variety of productivity indicators was made considering non-economic factors, various factors affecting the efficiency of international airports could be judged more comprehensively. The variables used by the authors are presented in Appendix 1.

Based on the assertions presented in this literature review, they examined airport efficiency utilising a range of inputs and outputs since they were related to numerous parameters such as the number of runways, passenger numbers, terminal area, amenities, revenue and costs. In other words, various indicators need to be used to analyse airport efficiency. We confirmed that research on this topic has continued for many years in various ways through literature studies.

3. Methodology and research design

3.1. TOPSIS

Numerous studies have been analysed mainly using DEA. It is one of the most frequently used technologies for measuring airport performance (Fasone and Zapata-Aguirre, 2016). The efficiency score, on the other hand, is vulnerable to even modest measurement errors because efficiency borders are defined by the actual performance of the highest-performing airports. If the sample size is small, a large proportion of airports will have an efficiency score of 1. While these problems could be effectively avoided by introducing virtual airports, which serve as the frontier between which efficiency of all airports is computed, DEA does not account for the underlying source of efficiency and inefficiency (Lam et al., 2009). DEA integrates operational and financial factors into inputs and outputs to analyse airport efficiency. Furthermore, studies using existing TOPSIS have only analysed the operational efficiency of airports in one country (Wang et al., 2004), or the financial efficiency of airports located on one continent (Ha and Moon, 2015). Hence, to compensate for these limitations, TOPSIS is utilised in this study to analyse the financial and operational aspects and derive the ranking of airports in ACI regions. This study suggests the possibility of adopting TOPSIS as one of the methodologies for analysing various airport efficiency.

From the collected data, TOPSIS techniques were employed to analyse the final performance of each airport. TOPSIS is one of the MCDA methods used in selecting alternatives that are closest to the Positive Ideal Solution (PIS) and farthest from the Negative Ideal Solution (NIS). If each property is monotonously increasing (or decreasing), TOPSIS has the advantage of being able to easily find an 'ideal' solution consisting of all the best attribute values and a 'negative' solution consisting of all the worst attribute values (Hwang and Yoon, 1981). TOPSIS also gives equal weight to all criteria and attributes, as well as measuring and aggregating the distance from the ideal outcome to reflect the outcomes (Yoon and Hwang, 1995). The study utilises TOPSIS to compute and select the airports corresponding to PIS and NIS, and to measure the distance at which other airports are separated from these criteria. It facilitates the argument that the closer each airport is to the PIS, or the farther away it is from the NIS, the more efficient it operates. Therefore, it is possible to assess the efficiency of the airport by finding PIS among the major international airports and ranking other airports from PIS.

3.1.1. Entropy weight

Before entering the process, the criteria weights were calculated. The entropy weight method, using entropy values from each metric, was used for this study since entropy weight is an efficiently objective weighting method for determining the weights of evaluation metrics. Specific methods for determining the weight of each evaluation indicator are as follows (Jin-qiang, 2019):

Step 1: Normalization of the arrays of a decision matrix to obtain the project outcomes X_{ij}:

$$X_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

Step 2: Computation of the entropy measure of project outcomes using the following equation:

$$E_j = -k \sum_{i=1}^{m} X_{ij} In\, X_{ij}$$

In which k = 1/In(m)

Step 3: Defining the objective weight based on the entropy concept:

$$w_{ij} = \frac{(1 - E_j)}{\sum_{j=1}^{n}(1 - E_j)}$$

3.1.2. The procedure for TOPSIS

The TOPSIS model facilitates computing the weighted alternatives to determine the standard decision matrix; these procedures divide into six steps (Hwang and Yoon, 1981). The weights by the process and the operational and financial performance of the entire airports are elaborated. Furthermore, the results were derived by separating operational and financial performance for detailed analysis. This analysis confirms whether there is a difference between the overall analysis and the analysis by sector.

The procedure for calculating TOPSIS after weight derivation is as follows (Al Kharusi & Başci, 2017).

Step 1: Determination decision matrix

Creating a decision matrix is required in the first step. In terms of a matrix, the rows contain decision points and are listed in order by success criteria. The column considers the evaluation factors that can be used in the decision-making process.

$$A_{ij}=\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}$$

In this matrix, m means the count of the decision points and n is the count of the evaluation factors.

Step 2: Standard decision matrix

The standard decision matrix can be calculated using the components of the A_{ij} matrix in step 1 and is described in the following formula.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}}$$

When the r_{ij} matrix is computed, it is possible to derive a new matrix, which is vector normalization, with the following new elements

$$r_{ij}=\begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix}$$

Step 3: Weighted standard decision matrix

At this stage, it is essential to identify the weight of all elements of the matrix (100% of the sum of all weighted elements). The criteria weight (w_i) associated with the evaluation factor can be calculated, and each element in each column must be multiplied by w_i Therefore, we can create the following new matrix called V Matrix.

$$\sum_{i=1}^{n} w_i = 1$$

$$V_{ij} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \dots & w_n r_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ w_1 r_{m1} & w_2 r_{m2} & \dots & w_n r_{mn} \end{bmatrix}$$

Step 4: Making solutions for ideal (A^+) and ideal (A^-)

Step 4 creates two solutions that set both positive and negative ideal solutions in the V matrix. This is relevant in determining alternatives, where at least (worst) values can be seen as the largest (best) weighted typically acceptable value choices. We utilize the maximum and minimum components to calculate the ideal solution for finding the best solution as follows:

$$A^+ = \left\{ (\max_i v_{ij} \middle| j \in J), (\min_i v_{ij} \middle| j \in J' \right\}$$

The above formula determines the A^+ ideal solution cloud, and for A^-, the ideal solution can be computed by the following formula:

$$A^- = \left\{ (\min_i v_{ij} \middle| j \in J), (\max_i v_{ij} \middle| j \in J' \right\}$$

In the two aforementioned formulas, J represents profit maximisation and J' indicates loss minimisation.

Step 5: Calculating the dimension of distinction

This is the step where the standard deviation of the decision point between the positive and negative dimensions should be calculated. There are two parts of the solution for each positive and negative aspect, which can be calculated using the Euclidean distance formula.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^* \right)^2}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}$$

S_i^+ and S_i^- indicate the distances from the ideal positive and negative solutions, respectively.

Step 6: Calculating ideal solutions of relative proximity

In this final step, we calculate relative proximity using the ideal negative and ideal distinctions.

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*}$$

C_i^* value must be between $0 \leq C_i^* \leq 1$ m and $C_i^* = 1$, and $C_i^* = 0$.

When the alternative value is close to a PIS, the value of C_i^* is close to 1. In contrast, if the alternative is the opposite, it is close to a NIS, and the value is close to 0. When calculating S_i^+, S_i^-, and C_i^*, all results must be ranked in descending order of value. It can be understood that if any C_i^* of each alternative has a distance from 1, it is placed too close to the positive ideal point. As C_i^* represents the efficiency scores for each alternative, the higher this value is, the higher efficiency is the level of the airport that is investigated (Jahanshahloo et al., 2009). Therefore, it is argued that these results outperform other airports.

3.2. Airport selection

This study selects for its analysis, airports in three major ACI regions (Asia, Europe and North America). Based on international air connectivity, cargo routes concentrated on a relatively small number of trade routes, with East Asia-North America and Europe-East Asia being the most prominent trade routes in the world (Boeing, 2020). In addition, airlines in the Asia-Pacific region are particularly expected to account for 42% of deliveries from North America and Europe, including 36% of passenger and cargo aircraft deliveries (Airbus, 2019). Therefore, the airports located in these three regions were adopted for investigation.

More than 1,000 airports worldwide can provide international routes, but smaller samples of airports need to be conducted for research (Pacagnella et al. 2021). In the case of

Asia, a total of six airports, BKK, HKG, ICN, NET, PEK, and SIN, were analysed, but BKK was excluded because data could not be obtained. These are the airports that handle the most passengers and cargo in Asia (Matsumoto and Domae, 2018). These airports were also used in the study of Ha and Moon (2015). Their study was analysed using TOPSIS, but they did not demonstrate what weight was employed, so these airports are analysed again using entropy weight.

Table 1.
The final list and average operational data from 2016 to 2019 of sample airports

Regions	Name of airports	Code (IATA)	Country	Number of cargoes (ton)	Number of passengers (thousand)	Air transport movements (thousand)
Asia (5)	Hong Kong International Airport	HKG	China	4,900	70,025	410
	Incheon International Airport	ICN	South Korea	2,838	64,819	373
	Narita International Airport	NRT	Japan	2,146	41,672	254
	Beijing Capital International Airport	PEK	China	2,001	97,794	603
	Singapore Changi Airport	SIN	Singapore	2,038	61,350	369
Europe (4)	Amsterdam Airport Schiphol	AMS	Netherlands	1,677	76,401	546
	Charles De Gaulle Airport	CDG	France	2,148	70,946	482
	Frankfurt Airport	FRA	Germany	2,171	66,338	491
	Heathrow Airport	LHR	UK	1,628	78,675	473
North America (8)	Hartsfield-Jackson Atlanta International Airport	ATL	USA	668	106,508	895
	O'Hare International Airport	ORD	USA	1,789	81,421	890
	Los Angeles International Airport	LAX	USA	2,339	85,271	699
	Charlotte Douglas International Airport	CLT	USA	173	46,734	555
	Denver International Airport	DEN	USA	275	47,564	600
	McCarran International Airport	LAS	USA	113	49,246	544
	Phoenix Sky Harbor International Airport	PHX	USA	380	44,641	436
	Toronto Pearson International Airport	YYZ	Canada	526	45,475	462

Source: Authors based on annual reports of sample airports

On the other hand, the number of sample airports in Europe was seven airports in total, AMS, BRU, CDG, FRA, LHR, LUX, and MAD. These airports have the highest connectivity in handling cargo in Europe (Boonekamp and Burghouwt, 2017). However, BRU, LUX, and MAD were excluded from the final sample because the financial statements of the three airports could not be secured. As a result, four European airports were selected as samples. Finally, in the case of sample airports in North America, the first analysis target was the ten airports utilised in Pacagnella et al. (2021)'s study. These samples were selected based on the level of movement at the airport, such as the total number of landings and take-offs. However, like several airports in Asia and Europe mentioned earlier, eight airports, excluding Dallas/Ft Worth International Airport and George Bush Intercontinental Airport, were utilised as final samples due to limited circumstances, such as the inability to collect financial statements. Therefore, the 17 airports in this study's three ACI regions are finally adopted for analysis as they are international airports performing hub functions (Boonekamp and Burghouwt, 2017; Matsumoto and Domae, 2018; Pacagnella et al., 2021). The final sample airports, including operational data, such as the number of cargoes and passengers and air transport movements, are reflected in Table 1.

3.3. Variable selection

3.3.1. Operational variables

Although many factors assess the operational performance of airports, data from each airport open to the public tends to be somewhat limited. As a result, this study assesses operational performance utilising publicly available data as well as other factors identified in earlier studies. The most frequently used variables in previous studies are number of runways, length of runways, cargo movement, number of passengers, length of terminals, and ATM (Wang et al., 2004; Barros and Dieke, 2008; Lozano et al., 2013; Chae and Kim, 2015; Lai et al., 2015; Fragoudaki and Giokas, 2016; Iyer and Jain, 2019; Wang and Song, 2020; Pacagnella et al., 2021). In the case of length of terminals, some airports did not disclose their exact terminal size, so the number of terminals was used instead as a final operational variable. Selecting these variables are justification for operational performance factors because correlation with variables affecting airport performance was found (Oum et al., 2003; Fasone et al., 2016).

3.3.2. Financial variables

The previous studies evaluated airport efficiency integrally using DEA. However, it was difficult to utilise direct variables because airport efficiency was analysed separately by input and output. Therefore, the aeronautical revenue per WLU, non-aeronautical revenue per WLU, operational profit per sales, and net profit per sales utilised by Ha and Moon (2015) had been adopted. The WLU is a measurement designed by Doganis et al. (1978), defined as one passenger processed or 100kg of freight handled. Unlike in the past, today's airports have varying needs and benefits for passenger handling based on the shopping commercialisation trend (Humphreys and Francis, 2002). Therefore, in addition to these variables, commercial income per passenger was adopted as the additional variable for financial analysis.

Table 2.
The final variables selection for analysis

Classification	Variables	Authors
Operational performance	Number of runways (OV1)	Oum et al. (2003), Lai et al. (2015), Iyer and Jain (2019), Baltazar and Silva (2020), Pacagnella et al. (2021)
	Length of runways, (thousand, m^2) (OV2)	Lozano et al. (2013), Lai et al. (2015), Fragoudaki and Giokas (2016), Iyer and Jain (2019), Wang and Song (2020)
	Cargo movements (OV3)	Oum et al. (2003), Lam et al. (2009), Chae and Kim (2015), Lai et al. (2015), Fragoudaki and Giokas (2016), Pacagnella et al. (2021)
	Number of passengers (thousand) (OV4)	Oum et al. (2003), Barros and Dieke (2008), Lozano et al. (2013), Chae and Kim (2015), Lai et al. (2015), Fasone et al. (2016), Fragoudaki and Giokas (2016), Bezerra and Gomes (2018), Baltazar and Silva (2020), Pacagnella et al. (2021)
	Number of terminals (OV5)	Chae and Kim (2015), Lai et al. (2015), Fragoudaki and Giokas (2016), Iyer and Jain (2019), Baltazar and Silva (2020), Wang and Song (2020)
	Aircraft movements (thousand) (OV6)	Oum et al. (2003), Lam et al. (2009), Lozano et al. (2013), Lai et al. (2015), Fasone et al. (2016), Fragoudaki and Giokas (2016), Bezerra and Gomes (2018), Baltazar and Silva (2020), Wang and Song (2020)
Financial performance	Aeronautical revenue per WLU (FV1)	Humphreys and Francis (2002), Chae and Kim (2015), Ha and Moon (2015), Iyer and Jain (2019)
	Non-aeronautical revenue per WLU (FV2)	
	Operational profit per sales (FV3)	Ha and Moon (2015)
	Net profit per sales (FV4)	
	Commercial income per passenger (FV5)	Humphreys and Francis (2002)
	EBITDA to debt ratio (FV6)	ACI (2012)
	EBITDA per passenger (FV7)	

Moreover, ACI (2012) suggest financial and commercial performance indicators, such as debt to EBITDA ratio and EBITDA per passenger. However, in the case of the debt to EBITDA ratio, a debt-related variable, if the resulting values are high, they affect negatively financial performance. Therefore, the debt to EBITDA ratio was converted to EBITDA to debt ratio and used as the final variable for uniformity of analysis. Airport performance was examined using data for four years, from 2016 to 2019. Data for analysis were obtained from individual airports by obtaining annual reports and financial statements. The final variables for analysis are shown in Table 2.

4. Result and discussion

4.1. The result of TOPSIS

The results for weights for the entire airport and variable are shown in Tables 3, 4 and 5.

Table 3.
Total annual and average (2016–2019) Entropy weight

Year	Operational Variables (6)						
	OV1	OV2	OV3	OV4	OV5	OV6	
2016	0.0179	0.0113	0.0611	0.0086	0.0513	0.0107	
2017	0.0174	0.0110	0.0594	0.0103	0.0496	0.0096	
2018	0.0222	0.0141	0.0749	0.0130	0.0584	0.0122	
2019	0.0217	0.0137	0.0705	0.0090	0.0570	0.0122	
2016–2019	0.0256	0.0162	0.0860	0.0123	0.0695	0.0143	
Year	Financial Variables (7)						
	FV1	FV2	FV3	FV4	FV5	FV6	FV7
2016	0.0769	0.0620	0.0885	0.1279	0.0947	0.3281	0.0609
2017	0.0665	0.0619	0.0951	0.1209	0.1085	0.3345	0.0553
2018	0.0733	0.0742	0.1175	0.1505	0.1184	0.1997	0.0716
2019	0.0671	0.0729	0.1179	0.1303	0.1453	0.2153	0.0672
2016–2019	0.0915	0.0884	0.0530	0.0512	0.1417	0.2898	0.0605

Table 4.
Total annual and average (2016–2019) Entropy weight of operational performance

Year	Operational Variables (6)					
	OV1	OV2	OV3	OV4	OV5	OV6
2016	0.1111	0.0704	0.3798	0.0534	0.3188	0.0665
2017	0.1106	0.0700	0.3778	0.0653	0.3153	0.0610
2018	0.1141	0.0723	0.3845	0.0667	0.2999	0.0625
2019	0.1178	0.0746	0.3830	0.0488	0.3096	0.0662
2016–2019	0.1143	0.0724	0.3840	0.0548	0.3105	0.0640

Table 5.
Total annual and average (2016–2019) Entropy weight of financial performance

Year	Financial Variables (7)						
	FV1	FV2	FV3	FV4	FV5	FV6	FV7
2016	0.0988	0.0797	0.1137	0.1644	0.1217	0.4216	0.0783
2017	0.0844	0.0786	0.1208	0.1535	0.1378	0.4249	0.0703
2018	0.0999	0.1012	0.1602	0.2051	0.1614	0.2722	0.0976
2019	0.0896	0.0973	0.1574	0.1740	0.1941	0.2875	0.0898
2016–2019	0.1279	0.1236	0.0740	0.0715	0.1980	0.4049	0.0845

The results of the overall airport ranking according to the TOPSIS process are shown in Table 6. The result shows that HKG was the most efficient of the 17 airports, while CLT airport was the lowest.

Table 6.
Total performance result of all airports

Airports	2016		2017		2018		2019		2016–2019	
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**
HKG	0.732	1	0.712	1	0.511	2	0.406	2	0.715	1
ICN	0.155	4	0.148	3	0.297	3	0.251	3	0.251	3
NRT	0.131	6	0.124	5	0.241	5	0.200	5	0.230	5
PEK	0.317	2	0.356	2	0.755	1	0.833	1	0.325	2
SIN	0.115	8	0.085	11	0.152	11	0.117	14	0.128	12
AMS	0.081	14	0.058	15	0.118	15	0.106	15	0.108	14
CDG	0.132	5	0.118	6	0.241	4	0.242	4	0.242	4
FRA	0.102	10	0.079	12	0.163	8	0.140	11	0.159	9
LHR	0.126	7	0.105	7	0.204	7	0.187	6	0.194	7
ATL	0.089	13	0.075	13	0.136	13	0.140	10	0.118	13
ORD	0.050	17	0.047	16	0.087	17	0.079	17	0.083	16
LAX	0.107	9	0.093	8	0.159	9	0.144	9	0.150	10
CLT	0.066	16	0.044	17	0.087	16	0.083	16	0.081	17
DEN	0.093	12	0.088	9	0.146	12	0.119	13	0.145	11
LAS	0.158	3	0.142	4	0.207	6	0.180	7	0.224	6
PHX	0.075	15	0.066	14	0.132	14	0.126	12	0.106	15
YYZ	0.099	11	0.085	10	0.153	10	0.144	8	0.159	8

The total result of operational performance in all airports is shown in Table 7. In terms of operational performance, LAX ranked the highest, indicating a trend similar to the total performance analysis results.

Table 7.
Total operational performance result of all airports

Airports	2016		2017		2018		2019		2016–2019	
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**
HKG	0.554	2	0.563	2	0.577	2	0.562	2	0.566	2
ICN	0.387	5	0.391	4	0.430	3	0.425	3	0.409	3
NRT	0.358	8	0.361	9	0.356	9	0.352	9	0.357	9
PEK	0.314	11	0.308	11	0.320	11	0.317	11	0.315	11
SIN	0.330	10	0.369	7	0.386	5	0.406	4	0.373	7
AMS	0.268	12	0.268	12	0.269	12	0.262	12	0.267	12
CDG	0.374	7	0.363	8	0.362	8	0.372	8	0.368	8
FRA	0.339	9	0.330	10	0.338	10	0.351	10	0.340	10
LHR	0.378	6	0.379	5	0.371	7	0.378	7	0.376	6
ATL	0.402	3	0.394	3	0.380	6	0.391	6	0.390	4
ORD	0.389	4	0.377	6	0.389	4	0.399	5	0.388	5
LAX	0.617	1	0.611	1	0.606	1	0.621	1	0.612	1

CLT	0.057	17	0.056	17	0.058	17	0.060	17	0.057	17
DEN	0.122	15	0.120	15	0.125	15	0.132	15	0.125	15
LAS	0.094	16	0.093	16	0.092	16	0.095	16	0.093	16
PHX	0.154	13	0.151	13	0.145	13	0.152	13	0.150	13
YYZ	0.138	14	0.139	14	0.143	14	0.146	14	0.141	14

The total result of financial performance in all airports is shown in Table 8. The result show that HKG is also located at the top, following the trend of total performance results.

Table 8.
Total financial performance result of all airports

Airports	2016		2017		2018		2019		2016–2019	
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**
HKG	0.736	1	0.715	1	0.507	2	0.396	2	0.724	1
ICN	0.149	4	0.142	4	0.289	3	0.242	3	0.242	3
NRT	0.125	6	0.118	5	0.235	4	0.193	5	0.225	6
PEK	0.317	2	0.357	2	0.787	1	0.875	1	0.325	2
SIN	0.108	8	0.074	10	0.132	11	0.091	14	0.106	11
AMS	0.074	12	0.049	15	0.104	14	0.095	13	0.094	13
CDG	0.126	5	0.112	6	0.234	5	0.237	4	0.236	4
FRA	0.094	10	0.070	11	0.150	9	0.125	10	0.146	10
LHR	0.119	7	0.097	7	0.194	7	0.177	7	0.185	7
ATL	0.071	15	0.055	13	0.108	13	0.117	12	0.083	14
ORD	0.018	17	0.017	17	0.035	17	0.033	17	0.031	17
LAX	0.072	14	0.055	14	0.090	15	0.077	16	0.079	16
CLT	0.066	16	0.043	16	0.089	16	0.084	15	0.082	15
DEN	0.093	11	0.088	8	0.147	10	0.119	11	0.146	9
LAS	0.159	3	0.142	3	0.210	6	0.182	6	0.228	5
PHX	0.073	13	0.064	12	0.132	12	0.125	9	0.104	12
YYZ	0.099	9	0.084	9	0.154	8	0.144	8	0.160	8

4.2. Discussion

HKG was the most efficient for the four-year period from 2016 to 2019, according to the average performance rating of airports. This outcome follows the same pattern as earlier research findings. Wang and Song (2020) presented an overall trend of efficiency reduction during the 2018–2021 forecast period, suggesting that HKG will be efficient. Lai et al. (2015) proved that HKG was the most efficient airport in terms of academics and practitioners. According to our result, the performance of HKG and PEK was noticeably higher compared to other airports. PEK has surpassed HKG since 2017, and its performance gap has continued to widen. The growth of other airports in the Bay Area, where HKG is located (Wong et al., 2017), and the commercial airspace control by the military have caused delays, which adversely affects HKG's competitiveness (LegCo, 2017). The 16 airports, excluding HKG, have experienced growth since 2017, but the trends have slowed down in the end except for PEK. As the performance of four airports in Asia was ranked within the top five except SIN, the trend proves the superior efficiency of airports in Asia.

These results demonstrate that airports in Asia have an advantage over other regions regarding passengers and cargo. According to the International Civil Aviation Organization (ICAO, 2019), passenger traffic in Asia and the Pacific accounted for 34.8% of global transportation, with 26.3% and 22.4% in Europe and North America, respectively. For cargo, Asia, Europe and North America, explained by trade volume, were 38.7%, 26.1% and 14.3%, respectively. Since the production infrastructure of automobiles and electronics, as well as global supply chains, are concentrated, trade volume confirms that Asia is higher than the rest of the world. According to International Air Transport Association (IATA), Asia's trade volume was 14.1M tones air cargo flown, Europe 9.9M tones air cargo flown, and North America 8.2M tones air cargo flown (IATA, 2020).

On the other hand, CDG airport was the most efficient airport, ranking fifth in 2016, sixth in 2017, fourth in 2018 and 2019, and experienced growth by achieving fourth on average in Europe. However, a similar trend was shown when limited to the four sample airports in Europe used in this study. Lai et al.'s (2015) study employed the AHP/DEA-AR technique to analyse the efficiency of 24 airports in Asia and Europe and analyse the efficiency of airports from academia and practitioner. Although the data they utilised were from 2010, the most efficient classified airports were CDG and LHR, followed by FRA and AMS, from the perspective of practitioners. However, as mentioned before, the final values for airports classified as efficient in DEA technology are 1. It means that the CDG and LHR show the same values. Therefore, unlike this study where TOPSIS was used, the exact final values were not calculated. In this study, CDG showed lower efficiency than LHR in operational performance, but they operated more efficiently than LHR in financial performance. In particular, CDG has been identified as the most efficient airport in Europe due to their high performance in terms of EBITDA per passenger and EBITDA to debt ratio. Due to this variable, the results of this study resulted in somewhat different results from previous studies (Lai, et al. 2015; Pacagnella, et al. 2021). Even though the efficient advantage of LHR is suggested in previous studies, the CDG has been analysed as the most efficient airport in Europe due to the two preceding variables recommended by the ACI.

In the United States, overall, all airports have achieved low levels, but the performance of LAS is noteworthy. They ranked third in 2016, fourth in 2017, sixth in 2018 and seventh in 2019, but slightly declined ever since. LAS serves as the first visitor gateway, and more than 40 airlines support passengers who wish to visit Las Vegas (Clark County Department of Aviation, 2021). According to the report regarding airport rankings released by The Wall Street Journal (2019), LAS had 58.33 points on WSJ SCORE, ranking sixth among the largest airports in the United States. The research found that their average domestic fare was the most affordable rate in the United States at $260.37, which explained that it was generating revenue by securing many domestic passengers.

According to Table 7, which shows the result of the operational performance of all airports, LAX was the most efficient airport, followed by HKG, ICN, ATL, ORD and LHR. We compared the study conducted by Pacagnella et al. (2021) for operational performance with our result. According to their study, PEK, LHR, and ATL showed superiority in infrastructure efficiency, and HKG, PEK, ATL, LHR, ATL, DEN and LAX were the most efficient operating airports in the flight consolidation section. Their efficiency score was 1, which became the reference airport in the DEA analysis. For the result, it is evident that their study shows slightly similar results to this study. However, their results, which used DEA, did not provide intuitive results on the airport rankings compared to ours that used TOPSIS. On the other hand, analysing using TOPSIS immediately identify differences in variables in the ranking of the subjects for analysis, which is the main reason this study adapted TOPSIS as a methodology to analyse the airport efficiency.

Conversely, it is identified that there is no noticeable change in the operating performance of the airport over the period, as shown in Table 7. This result means that operational performance may continue if not affected by an exceptional or unmanageable external environment, such as COVID-19. Inevitably, large or hub airports with high proportions of cargo and aircraft movement or passenger numbers exhibit high operational performance. As reflected in Table 9, ATL, PEK, ORD and LAX have an advantage over the rest of the airports regarding passenger numbers and aircraft movement. HKG has an overwhelming advantage in cargo movement. These airports also emerged at the top of previous studies. Their advantages are often published in their annual reports. However, as the criteria for assessing the performance of airports are wide-ranging and divided into diverse groups (Baltazar et al., 2018), it may only be appropriate to evaluate them on ostensibly published operational performance, including aircraft and cargo movement and passenger numbers.

Table 9.
The operational performance of sample airports from 2016 to 2019

Index	Airport	Number of runways	Length of runways (thousand, m²)	Cargo movements (tons)	Number of passengers (thousand)	Number of terminals	Aircraft movements (thousand)
Asia (5)	HKG	2	456	4,900	70,025	1	410
	ICN	3	690	2,838	64,819	1.5	373
	NRT	2	390	2,146	41,672	3	254
	PEK	3	616	2,001	97,794	2	603
	SIN	2	480	2,038	61,350	3.75	369
Europe (4)	AMS	6	933	1,677	76,401	1	546
	CDG	4	702	2,148	70,946	3	482
	FRA	4	726	2,171	66,338	2	491
	LHR	2	378	1,628	78,675	5	473
North America (8)	ATL	5	687	668	106,508	7	895
	ORD	8	1,111	1,789	81,421	4	890
	LAX	4	645	2,339	85,271	9	699
	CLT	4	507	173	46,734	1	555
	DEN	6	1,014	275	47,564	1	600
	LAS	4	614	113	49,246	2	544
	PHX	3	415	380	44,641	3	436
	YYZ	5	929	526	45,475	2	462

Source: Authors based on annual reports of sample airports

The clues to this phenomenon are identified through comparisons between the airports' financial and overall performance. In the case of financial performance, a similar trend with the results of total performance is depicted (Figure 1). This result leads to one assumption: for operational performance, the length of the runway, the number of runways and the number of terminals have remained unchanged over the four years. Changes had occurred only in the case of passengers, cargo and aircraft movement, which may not affect the outcome of the analysis.

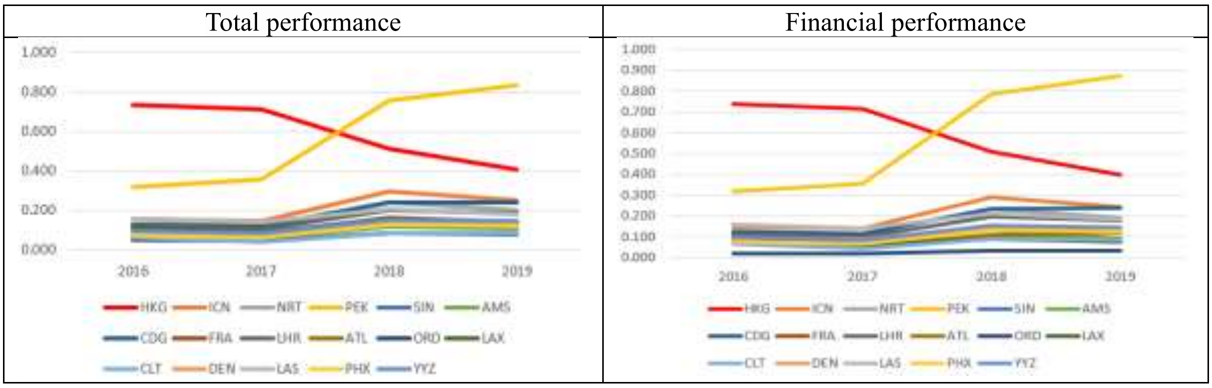

Figure. 1. Total and financial performance trends at all airports from 2016 to 2019

Table 10 reflects data on the financial performance of the sample airports. The airports with the highest performance for aeronautical revenue per WLU were identified in LAS, LHR, and CLT, respectively. In terms of the non-aeronautical revenue per WLU, it was found that airports in North America, such as LAS, DEN, and YYZ, achieved high performance. Overall, Asian airports remained in lower positions. Generally, as airport fees for transit passengers are lower than standard fees, aeronautical revenues may decrease as the proportion of transit passengers in Asia to the total increase in passengers (Chae and Kim, 2015). Non-aeronautical revenue excludes landing and passenger fees from total revenue (Chae and Kim, 2015), with airports in Asia being more vulnerable than those in Europe and North America. Non-aeronautical revenue has a significant positive impact on airport operations and financial efficiency (Chae and Kim, 2015), and disregard of airport operators for non-aeronautical revenue development tends to lead to reduced efficiency at airports (Liu, 2016; Iyer and Jain, 2019).

Table 10.
The financial performance of all airports from 2016 to 2019 ($ Millions, %)

Index	Airport	Aeronautical revenue per WLU	Non-aeronautical revenue per WLU	Operational profit per sales	Net profit per sales	Commercial income per passenger	EBITDA to debt ratio	EBITDA per passenger
Asia (5)	HKG	18.857	31.6	0.522	0.442	2.543	377.4	23.072
	ICN	26.346	59.532	0.532	0.406	19.08	40.3	19.529
	NRT	49.239	49.752	0.345	0.13	20.294	19	18.182
	PEK	35.95	38.991	0.344	0.239	3.806	134.5	7.447
	SIN	35.241	55.474	0.361	0.258	3.319	29.8	15.344
Europe (4)	AMS	59.85	41.8	0.256	0.206	3.051	27	9.653
	CDG	97.353	110.861	0.259	0.152	17.552	38.6	26.031
	FRA	50.898	115.194	0.218	0.135	8.674	32.2	18.659
	LHR	140.803	95.454	0.399	0.104	11.283	13.5	27.6
North America (8)	ATL	4.562	117.33	0.638	0.139	1.084	5.9	2.01
	ORD	39.241	38.284	0.036	0.066	1.004	2.7	3.939
	LAX	38.448	34.339	0.174	0.255	5.309	8	7.249
	CLT	47.653	137.602	0.116	0.213	1.083	16.7	3.264
	DEN	131.612	250.302	0.106	0.13	1.601	5.2	6.336
	LAS	242.828	377.466	0.141	0.101	1.47	6.4	5.938
	PHX	41.306	64.756	0.68	0.043	0.745	25.8	11.857
	YYZ	95.835	174.044	0.307	0.079	10.558	10.5	15.534

Source: Authors based on financial statements and annual reports of sample airports

Regarding commercial income per passenger, NRT, ICN, CDG, and LHR recorded remarkable growth. An increase in commercial-based indicators reflects the financial direction of the airport. These measures also include commercial concessions and duty-free income measures, reflecting the diversification of businesses and subsequent management drives to satisfy shareholders under the new commercial and privatized ownership structure (Humphreys and Francis, 2002). In the early 20th century, new terminal retail arrangements became sandwiched between landside and airside, and they began to look similar to large anchor department stores (Marquez, 2019). It has been argued that managers should meet travellers' expectations of enjoying shopping and leisure in commercial areas and allow them to stay there as much as possible during their waiting times to generate revenue for the airport (Fasone et al., 2016; Martín-Cejas, 2006). For example, Incheon International Airport carefully arranged 600 brand stores in a space of 17,074 square meters to provide customers with an optimized shopping route. Sales at their duty-free shops have been growing at an annual average rate of around 15 percent since their opening in 2001 (Incheon International Airport Corporation, 2017). However, there is also criticism of the commercialization of airports. Graham (2018) argued that it is difficult to fully determine whether the airport's heightened expectations were caused by consumers' genuine need or desire for facility expansion or whether the airport's efforts to maximize commercial income by becoming a shopping center only changed passengers' expectations. Most passengers will try to reduce the uncertainty and congestion of security filters while spending the least amount of time on the concourse (Marquez, 2019). The travelling public does not favor them because they want to get through the airport as soon as possible from the interference of many shops and restaurants (Graham, 2018). One of the leading causes of delays is congestion on the airside and landside, which has a significantly negative impact on airport efficiency. Regarding non-aeronautical revenue, the negative impact of congestion may be higher than the negative impact of delay. However, aeronautical charges tend to be higher at congested airports as delays caused by congestion must be compensated at the airport under contract with the airline (Adler and Liebert, 2014; Iyer and Jain, 2019).

Meanwhile, the airports in Asia and Europe were predicted to outperform those in North America in profitability. In particular, the performance of Asian airports is noteworthy. Their superiority in cargo and aircraft movement, commercial income, and the number of passengers led to significant financial performance. Since the landing fee is directly related to the airport's aeronautical revenue, the higher the landing fee, the higher the profit. Therefore, the higher aircraft movement could trigger higher aeronautical revenue (Chae and Kim, 2015). Asian and European airports have had effective financial operations. Among them, the performance of airports in China is noteworthy such as HKS and PEK. The variables related to EBITDA used in this study are EBITDA to debt ratio and EBITDA per passenger. EBITDA is often used to determine a company's financial standing (Prusak, 2018). It is a commonly used measure of financial leverage, where the higher the debt level, the less flexible the airport spending is and the borrowing costs are higher. Airports with recently completed significant capital development programs will likely have a higher debt to EBITDA (ACI, 2012). LAX launched the Terminal 1.5 project to address congestion and inconvenience to customers (Los Angeles World Airports, 2016). LAX's effective operation will be likely if this problem with traffic congestion is resolved.

As previously confirmed, there were no noticeable changes in the number of passengers, cargo movement or aircraft movement at individual airports. Therefore, differences in changes in financial variables for each airport may affect the total outcome. However, these results suggest that operational performance may not be proportional to financial performance, so it may be argued that integrated and detailed analyses should be performed separately for each sector. The literature review shows that various previous studies analysing airports' performance did not utilise the debt-related indicators of airports, and this is essential because it demonstrates the financial health of the company to investors and companies related to their industry (Atrill and McLaney, 2017). This study also employed these indicators because ACI recommends debt-related key indicators as financial and commercial indicators for airports, such as debt to EBITDA ratio and EBITDA per passenger (ACI, 2012). The results of studies analysing airport performance and efficiency are somewhat different. It employs the same methodology but confirms that a more extensive study is available depending on the variable utilised, demonstrating that the results change depending on various parameters. Therefore, the results of studies using debt-related variables are remarkably different from the findings of other studies.

5. Conclusion

The COVID-19 pandemic in December 2019 reduced air transport demand, causing global airlines to have a dreadful first quarter of 2020 (ICAO, 2021). Aviation-related industries are also experiencing a slowdown in business. The risk of bankruptcy is fast increasing, and while the business recession persists for a year, connected business owners need help to establish and implement planned operations (Pereira and Soares de Mello, 2021; Gudmundsson et al., 2021). For appropriate countermeasures, it is essential to evaluate airport performance in advance (Humphreys and Francis, 2002). As a result, research on operational and financial efficiency for major airports is required to provide various participants with the necessary basis to modify strategies and change the course of their business. Therefore, this study demonstrated an overall description of the airport industry and analysed the factors affecting airport performance through a literature review. To explain research questions, airport performance in the three regions was analysed by dividing it into operational and financial factors and overall performance through the TOPSIS model.

There were three questions in this study. First, which airports are considered to efficiently operate in terms of international and hub airports? Based on the literature review, this study identified that 22 airports in Asia, Europe, and North America efficiently play their roles as international and hub airports. However, due to the difficulty of securing data, the final 17 airports were adopted, and HKG was analysed as the most efficient airport. Overall, Asian airports performed well, while certain North American airports were found to be inefficient. This may be due to the decentralization of airports due to the prominent regional characteristics of North America. The operational performance of Asian and European airports as international airports was concentrated because only one airport in each country was included in the sample.

Second, will there be differences in airports' performance based on sector-specific analysis? Differences were found between sample airports' overall and operational or financial performances. The efficiency ranking of operational performance, which means the airports' connectivity, remained constant. Conversely, changes were detected in their financial performance. For instance, ATL, ORD, and LAX in North America were efficient airports in terms of operational performance. However, their financial performance remained low. Moreover, DEN, LAS, PEK, and YYZ were identified as relatively efficient airports in operational performance, although their financial performance was low. This phenomenon affected the overall efficiency. Therefore, analyzing airports only using operational criteria such as runway, aircraft and cargo movement, and the number of passengers means their connectivity could be more efficient.

Finally, what are the differences between variables and methodologies utilized in previous studies and other variables and methods? This study used runways, terminals, aircraft and passenger movement, and passenger numbers used in many studies as variables to measure operational efficiency. However, different variables that had not been used for a while in other studies were adopted to measure financial efficiency. For instance, WLU was utilized in aeronautical and non-aeronautical revenue, and sales at the airport were reflected concerning operating and net profit. Furthermore, the EBITDA related to the company's financial position reflected the liabilities and passengers at each airport. Although many airports disclose data in their favor through their annual reports, this study demonstrates a wide range of data, causing it to differentiate itself from other studies. This is the justification for this study compared to other studies. Additionally, unlike other studies using DEA, TOPSIS was utilized to present results that intuitively verify the efficiency of sample airports. Moreover, it created a basis for separating operational and financial performance and measuring them on various criteria.

The contributions of the study are as follows. First, this study has utilised the latest data rather than previous research. It allows airport stakeholders to identify recent performance trends in airport performance. Second is the need for analysis combined with connectivity (productivity) and additional categories. Although this study did not reflect the recent decrease in air travel due to COVID-19 (ICAO, 2021), aircraft and cargo movements and passengers at each airport had previously remained constant without significant changes. However, differences were detected in the analysis through the financial category, which is an additional category. In particular, cases with high connectivity but low financial performance were confirmed, and vice versa. Therefore, it is necessary to include categories such as service quality measured by delay and dwell time. Finally, this study used financial factors that are different from previous studies. In most of the existing studies, total revenue and operating income have been adopted as variables for measuring financial performance. However, this study analysed them as well as aviation and non-air revenue, commercial revenue, and EBITDA. As a result, it was confirmed that the performance of airports with high commercial profits was generally high. This study also found that low debt to EBITDA meant that those projects were embarked on recently. Therefore, airport officials should improve the service and satisfaction of passengers and secure commercial profits for the airport's growth.

Moreover, the study identified many differences in the performance results of airports presented in academia, institutions, and the media. Currently, various variables are utilised to measure the performance of airports and variables are being derived and developed for better measurement. Although airport-related organisations such as ACI encourage measuring variables, many airports do not provide this information, making research impossible. This suggests that academia and institutions can investigate in various ways by using data, other than those related to airport connectivity, which is published to promote the performance of airports. Therefore, academia and institutions should establish standards to build a foundation for continuous and consistent analysis and encourage airports to provide this information.

This study attempted to investigate the operation and financial performance of principal airports worldwide using TOPSIS. Additional analysis was conducted in terms of operational and financial performance. Nevertheless, this study implies the following limitations. First, the number of sample airports analysed in the study is limited due to the difficulty of obtaining data and it cannot represent the entire airport. Second, this study did not include variables that could measure airport service levels, such as delay and dwell time. The airports are using shopping centers and duty-free shops for commercial profits; however, the congestion and delays at airports could trigger passenger anxiety. Therefore, it may not be linked to commercial revenue because it can limit the desire for shopping (Graham, 2018). LAX had the highest operating performance but remained at the bottom of the list regarding financial performance. There are several problems behind this superior operational performance, such as bad customer experience, complicated layout, and traffic congestion.

According to the Airport Satisfaction Survey conducted by Power (2017), LAX ranked 17th among the eighteen mega airports in the United States. Overall, many customers are not satisfied with it. Therefore, further studies are required, including other variables such as delay and dwell time related to passenger service levels and satisfaction. Lastly, this study implemented TOPSIS as a single methodology with secondary data, as the coronavirus has made it difficult to interview airport-related industrial employees. With the broad usage spectrum of TOPSIS, it is utilised in various fields but requires specific weight vectors through specialists. However, since this study designated weight only through numerical calculations and did not accept the empirical theory of experts (Paradowski et al. 2020), it is necessary to designate weight using opinions between academia and practitioners. Hence, the need for further research has been raised to overcome these limitations of the study. An additional methodology to reflect the opinions of different stakeholders will support identifying airports that operate most efficiently from their perspective.

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Appendix 1. Literature on efficiency variables of airport performance

Paper	Sample	Variables (input)	Variables (output)
Humphreys and Francis (2002)	-	- Revenue: Traffic income per passenger, Traffic income per WLU, Traffic income per turnover, Commercial income per passenger, Concession income per passenger, Duty- and Tax-free income per international departing passenger, Other concession income per Passenger, Property income per passenger, Property income per workload unit - Cost: Staff cost/employee, Passenger/employee, WLU per employee, Staff cost per passenger, Staff cost per WLU, Other direct costs per passenger, Other direct costs per WLU	
Oum et al. (2003)	50 airports in Asia-Pacific, Europe and North America	No. of employees, No. of runways, terminal size, No. of gates, and soft cost input	Aircraft movements, No. of airport passengers, cargo volume and a quantity index for non-aviation-related revenue
Barros and Dieke (2008)	31 airports in Italy	Labour costs, capital invested, operational costs excluding labour costs	No. of planes and passengers, general cargo, handling receipts, aeronautical sales, commercial sales
Lam et al. (2009)	11 airports in Asia	Labour, capital, soft input, trade value	No. of aeronautic movements, passengers and tonnes of cargo
Chae and Kim (2015)	11 airports in Asia	- Operational input: No. of employees, passenger terminal, cargo terminal - Financial input: labour, depreciation, amortisation, soft cost	- Operational output: passenger numbers, cargo throughput, non-aeronautical revenues. - Financial output: aeronautical revenues, non-aeronautical revenues
Ha and Moon (2015)	6 airports in Asia	Aero revenue per WLU, Non-aero revenue per WLU, Passenger growth rate, Freight growth rate, Operational profit per sales, Net profit per sales	
Lai et al. (2015)	24 airports	No. of employees, No. of gates, No. of runways, size of terminal area, length of runway and operational expenditure	No. of passengers, amount of freight and mail, aircraft movements and total revenues
Fasone et al. (2016)	15 airports in Germany	No. of total passengers, passengers of domestic routes, passengers to European routes, passengers to other international routes, low-cost carrier passengers, passengers other than LCC, movements and airlines operating in the airport, overall surface of commercial activities, surface of non-aviation activities, No. of retail shops and restaurants	Logged non-aviation revenues per passenger and logged non-aviation revenues per square metre (EUR)
Fragoudaki and Giokas (2016)	38 airports in Greece	Runway length, apron size and passenger terminal size	No. of passengers, aircraft movements and tonnes of cargo
Iyer and Jain	61 articles	Capital assets, capital invested, labour cost, material cost,	Aeronautical revenue, commercial revenues, ATM, cargo,

(2019)		operating cost, soft cost, annual capacity of terminal, apron area, apron stands, baggage collection belts, boarding gates, check-in counters, dynamic apron capacity, FTE employees, maximum throughput capacity, runway area, runway length, runways, scheduled routes, terminal area, total airport area	mail, passengers, WLU
Pacagnella et al. (2021)	50 airports in six ACI regions	Infrastructure, the terminal area, the No. of aircraft spaces, No. of runways, the total people working, consolidation of landings, take-offs per year, No. of landings and take-offs	No. of landings and take-offs, No. of passengers and cargo transit
Lozano et al. (2013)	39 airports in Spain	Total runway areas, apron capacity, No. of boarding gates, baggage belts and check-in counters Intermediate product: aircraft traffic movements	- Desirable output: Annual passenger movements and cargo handled - Undesirable output: No. of delayed flights and accumulated flight delays
Bezerra and Gomes (2018)	94 airports in Brazil	Airport efficiency/productivity, service quality, safety performance, security issues, economic-financial aspects, environmental issues	
Wang and Song (2020)	8 airports in China and 4 airports in Asia	Runway area, passenger terminal area Intermediate outputs/inputs: processed passengers, processed cargo, aircraft movements	Airport total revenues, airport net income
Wang et al., (2004)	10 airports in Taiwan	- Employee productivity: No. of take-offs and landings to No. of employees, Cargo tonnage to No. of employees, Floor area of terminal building to No. employees, Revenue to No. of employees, Non-aviation income to No. of employees, No. of passengers to No. of employees - Airline service level: Floor area of terminal to No. of airlines, Size of apron to No. of airlines, Volume to No. of airlines, Volume to No. of take-offs and landings, Volume to the No. of routes, Service standards of runway - Passenger service level: Take-offs and landings to No. of passengers, No. of airlines to No. of passengers, No. of routes to No. of passengers, No. of car parks to the No. of passengers during peak hours, Degree of congestion, No. of boarding gates to No. of passengers, No. of check-in counters to No. of passengers - Aviation and fire service level: No. of police and firefighters to No. of take-offs and landing, No. of police and firefighters to No. of airlines, No. of police and firefighters to No. of passengers, No. of police and firefighters to floor area of terminal, No. of police and firefighters to No. of car parks, No. of police and firefighters to the size of the apron, No. of police and firefighters to No. of flight routes, No. of aviation controllers to the No. of take-offs and landings, No. of aviation controllers to No. of flight routes	
Baltazar and Silva (2020)	4 airports in Spain	Six KPA: core, safety and security, quality, productivity/cost effectiveness, financial/commercial, environment	