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Performance evaluation of the global airline industry under the impact of the COVID-19 pandemic: A dynamic network data envelopment analysis approach

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ABSTRACT

The COVID-19 pandemic posed unprecedented challenges to the airline industry, necessitating a focus on maintaining high efficiency for profitability. This study assesses the efficiency of 26 international airlines from 2019 to 2022 using a dynamic network data envelopment analysis (DNDEA) methodology. The model accounts for the dynamic effect between two consecutive periods and incorporates an internal structure to evaluate airline performance across multiple dimensions. It enables the assessment of overall, period-specific, and stage-specific efficiencies. The findings reveal that while overall efficiency is moderately high on average, no airline achieved full efficiency during the pandemic. Efficiency decreased notably from 2019 to 2020, with a partial recovery but not a return to pre-pandemic levels by 2022. Operational performance remains satisfactory and stable, while service and financial performance exhibit lower efficiency, especially among low-cost airlines compared to full-service counterparts. Additionally, the study explores airlines' environmental impact by considering greenhouse gas emissions. Comparative analysis with a dynamic DEA model without internal structure highlights theoretical contributions, and the study offers managerial insights for airline leaders and policymakers.

1. Introduction

The onset of the COVID-19 pandemic posed unprecedented challenges to the airline industry. Global measures like travel restrictions and changing passenger behaviours significantly affected travel demand and airline operations (Albers and Rundshagen, 2020). The International Air Transportation Association (IATA) reported a global passenger number decline of 60.2% in 2020, with the Middle East and Europe experiencing the most significant drops at 67.6% and 67.4%, respectively (IATA, 2021). Global airline passenger revenue plummeted by 69% from 2019 to 2020. While there was a partial recovery in subsequent years, revenue passenger kilometres in 2022 were only 68.5% of pre-pandemic levels (IATA, 2023).

Performance evaluation, as a systematic process, involves the analysis of a company's outputs about the resources utilised in its business activities (Dinçer et al., 2017). This evaluation aims to assist airlines in identifying areas for improvement (Schefczyk, 1993). In the context of this study, the focus is on assessing efficiency changes within the framework of the COVID-19 pandemic. Through performance evaluation, this research endeavours to provide practical recommendations to airline management for enhancing efficiency, particularly when confronted with similar challenges in the future.

Airlines' profitability is intricately tied to efficiency due to their heavy reliance on resources like fuel and labour (Schefczyk, 1993). The pandemic disrupted airline operations and performance by reducing income, further influenced by natural disasters, regulations, oil prices, and competition (Sadi and Henderson, 2000). Recent research has investigated how events, such as aviation's participation in the European Union Emission Trading Scheme (2008–2012) and the "Carbon Neutral Growth from 2020″ strategy (2008–2015), impact airline

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performance, as explored by Li et al. (2016) and Cui and Li (2017c).

Recent years have seen a shift in focus from operational and financial efficiencies to environmental efficiencies in airline studies (Wang et al., 2017; Li et al., 2016). This change is driven by the carbon emissions from air transport, which accounted for 2% of global emissions in 2022 (IEA, 2022). Airlines are now committed to eliminating airline emissions, by performing vital assessments considering environmental factors, alongside operational and financial aspects.

This study employs Data Envelopment Analysis (DEA) as the analytical tool for assessing airline performance. DEA, introduced by Chang et al. (2014), is a nonparametric method that calculates efficiency by considering multiple inputs and outputs. DEA offers a notable benefit in that it does not rely on predetermined input and output weights, thus diminishing the subjectivity inherent in evaluating performance. Furthermore, DEA permits the integration of variables with varying units of measurement, thereby improving the comparability of data (Schefczyk, 1993). However, recent years have seen growing recognition of limitations in the standard DEA model (Mallikarjun, 2015). It often treats decision-making units (DMUs) as "black boxes," lacking explanatory power and struggling to identify inefficient DMUs (Kremantzis et al., 2022b; Kremantzis et al., 2022a; Xiao et al., 2024). Furthermore, it neglects dynamic effects and resource flows between consecutive periods (Kao, 2013). In response, dynamic network DEA models have emerged to address these shortcomings, elucidating DMU processes and connecting consecutive periods (Tone and Tsutsui, 2014; Omrani and Soltanzadeh, 2016).

While the dynamic network DEA method has found recent application in studies by Yu and Nguyen (2023) and Losa et al. (2020), there needs to be more in its use for assessing airline efficiencies within the unique context of the COVID-19 pandemic so as to provide more specific analyses and insights. Moreover, only a few studies have examined airline efficiency during the pandemic using alternative DEA models. For example, Kaffash and Khezrimotlagh, (2023) investigated the performance of US airlines in 2019 and 2020 under the pandemic's influence, employing a network DEA model that decomposed the airline production process into profitability and marketability stages. However, their study focused solely on overall efficiency scores and did not delve into the efficiency of each sub-stage, missing the opportunity for deeper insights. Furthermore, it calculated efficiency scores for individual years but overlooked the dynamic factors spanning 2019 and 2020. Addressing this research gap, our study introduces an empirical evaluation model based on (Omrani and Soltanzadeh, 2016) relational dynamic network DEA model. This model aims to enable the measurement and comparison of global airlines' performance across various dimensions during the critical period of 2019–2022.

This research study adopts a multifaceted approach to comprehensively assess global airline efficiency amidst the COVID-19 pandemic. This evaluation encompasses four pivotal dimensions: operational, service-related, environmental, and financial. To achieve this assessment, our study is structured around the following objectives. Firstly, we construct an empirical dynamic network DEA model, building upon the theoretical framework established by Omrani and Soltanzadeh (2016). Secondly, we conduct a comparative analysis taking into consideration global airlines' overall efficiency, efficiency specific to distinct time periods spanning from 2019 (pre-pandemic era), to 2022 (post-pandemic period), and efficiency pertaining to various production stages. By delving into these dimensions, we intend to unravel the dynamic nature of airline performance, pinpointing the temporal and stage-specific facets that contribute significantly to overall efficiency. Lastly, this research seeks to extract practical and actionable insights from the findings generated by the DEA model. These insights will illuminate efficiency shifts, directing attention to the production stages within airlines where notable inefficiencies persist, thereby offering meaningful observations for the enhancement of the airline industry as a whole.

The remainder of this study is organised as follows. In Section 2, existing airline performance evaluation methods are reviewed, focusing on DEA-related approaches. Section 3 introduces the methodology, covering theoretical foundations, empirical model construction, variable selection, and data collection. The empirical model's results are presented in Section 4. Section 5 discusses theoretical contributions and managerial implications. Finally, Section 6 provides the conclusion, addressing limitations and suggesting future research pathways.

2. Literature review

2.1. Evaluation of airline performance

In recent years, scholars have utilised various methods to evaluate airline performance, including multiple criteria decision-making (MCDM), data envelopment analysis (DEA), stochastic frontier analysis (SFA), and structural equation modelling (SEM) (Pineda et al., 2018; Arjomandi and Seufert, 2014; Assaf, 2009; Jenatabadi and Ismail, 2014). Table 1 summarises and presents several existing approaches along with relevant literature examples.

MCDM is commonly used but relies on expert judgment to determine evaluation criteria and weights, which can introduce bias and hinder reliability. Studies often focus on criteria selection and weight determination. For example, (Chen, 2016) introduced an improved MCDM model for assessing airline service quality in Taiwan. Pineda et al. (2018) developed an integrated MCDM model using data mining to extract relevant criteria from historical data for accurate airline performance evaluation.

Other scholars have employed quantitative methods like DEA to assess airline performance. For example, Arjomandi and Seufert (2014) used bootstrapped DEA to evaluate the environmental and technical performance of 48 global airlines from 2007 to 2010. They found that Chinese and North Asian airlines were generally more technically efficient, while European airlines excelled in environmental efficiency. Also, low-cost airlines tended to be more environmentally efficient than full-service airlines. Choi et al. (2015) introduced a service quality-adjusted DEA model to assess the operational efficiency of 12 American airlines. This study incorporated service quality as an output variable to investigate its relationship with productivity in the airline industry, highlighting the potential for a balance between efficiency and service quality.

This study opts for the DEA approach to evaluate airline performance due to its practical advantages. Different from other aforementioned models used for similar analytical tasks, DEA is a non-parametric approach that does not make any assumptions about functional forms or statistical properties, reducing the risk of errors (Coli et al., 2011). It can handle multiple inputs and outputs with different scales, identifying efficiency targets for inefficient companies (Kaya et al., 2023). DEA's reliance on linear programming makes it user-friendly and feasible, especially for managers without a technical background.

2.2. Application of DEA in evaluating airline efficiency

2.2.1. Standard DEA model

Since Schefczyk (1993) first utilised a standard DEA model to assess the operational performance of 15 airlines, the DEA approach has found widespread use in numerous studies for airline performance evaluation. However, the conventional DEA models often suffer from the limitation in their ability to effectively distinguish the efficient DMUs (Ratner et al., 2023; Kao, 2013). Consequently, most studies employed modified DEA models to address this limitation. For example, Kaya et al. (2023) employed a super-efficiency DEA model to assess the performance of 35 airlines, while Chang et al. (2014) employed a slacks-based DEA model for global environmental and economic performance evaluation of 27 airlines.

Table 1
Existing methods of evaluating the airline performance.

Methodology	Literature	Samples	Key variables	Key outcomes
Multiple criteria decision-making (MCDM)	Barros and Wanke (2015)	29 African Airlines, 2010–2013	number of employees, total number of aircraft, operating costs, with a negative impact on efficiency levels, RPKs and RTKs with a positive impact on efficiency levels	African airlines generally demonstrate a low average efficiency, with considerable variations. The primary determinant of airline efficiency is the size of their network.
	Pineda et al. (2018)	12 American airlines, 2005–2014	Operational and financial variables	Both internal operational and financial factors form the starting point for efficiency improvement. Criteria like stock price and net income should be given high weights in the proposed MCDM evaluation model.
Stochastic Frontier Analysis (SFA)	Good et al. (1995)	8 European airlines and 8 American airlines, 1976–1986	labor, energy and other materials, aircraft fleet, load factor, stage length, measure of network size, percent of the fleet which is wide bodied, percent of the fleet which uses turboprop propulsion	During the period of European deregulation, European airlines exhibited similar efficiency levels with their American counterparts.
	Assaf (2009)	12 Major U.S. airlines, 2002–2007	total operational cost, labour cost, aircraft fuel and oil expenses, number of planes, load factor, total operating revenue	The performance of U.S. airlines exhibited decline from 2002 to 2007, and they were not operating at an optimum level.
Data envelopment analysis (DEA)	Choi et al. (2015)	12 U.S. airlines, 2008–2012	total no. of employees, available seat miles, revenue passenger miles, operating revenue, service quality index,	Airlines can strike a balance between service quality and productivity. Budget airlines can benefit from marginal service improvement, while it is harder for full-cost airlines to meet passengers' service expectations.
	Arjomandi and Seufert (2014)	48 global airlines, 2007–2010	labour, capital, TKA, CO2-e emission	Chinese and North Asian airlines outperformed the technique efficiency, while European airlines performed best in environmental efficiency.
Structural equation modelling (SEM)	Jenatabadi and Ismail (2014)	209 airlines	HDI, GDP, load factor, operating profit, RPK, market share, vehicle kilometre, advertising, length, departure, inflation	The economic situation has a great impact on airline performance and affects internal operations.

2.2.2. Network DEA model

Traditional single-stage DEA models have limitations as they treat airlines as black boxes, assessing overall efficiency. Airlines have complex multi-stage operations. Multi-stage network DEA models address this by identifying specific improvement areas. For instance, Zhu (2011) introduced a two-stage network DEA model to assess airlines performance, first measuring resource efficiency and then revenue generation. Mallikarjun (2015) introduced a three-stage network DEA model to assess operational efficiency in 27 US airlines in 2012. The model divided airline operations into operation, service, and sales stages. The operation stage gauged cost efficiency, the service stage evaluated service effectiveness, and the sales stage measured revenue generation. Other researchers have also adopted this framework (Li et al., 2016; Li et al., 2016; Cui and Li, 2017c). Yet, these studies primarily use the network DEA model for more precise efficiency scores, failing to fully exploit its capability to identify the critical stages with the most significant impact on airline efficiency alterations.

2.2.3. Dynamic DEA model

The standard DEA model evaluates the efficiency of a DMU within multiple periods in a static fashion. Without consideration of the interrelations of these periods, the generated efficiency results can be misleading (Kao, 2013). When tracking efficiency changes over time, it is essential to use time-sensitive techniques like DEA window analysis and the Malmquist index, (Tone and Tsutsui, 2010), rather than relying solely on the static DEA model. Peoples et al. (2023) used the Malmquist index to study airline efficiency over time and found that low load factors decrease productivity. Although the time effect is considered in such methods, they still treat each period separately and do not consider the connection between consecutive periods.

In practical airline operations, strategic resource allocation and capital investment planning requires a holistic approach, making the standard DEA model's individual period assessment less ideal. Färe and Grosskopf (1997) introduced the dynamic DEA model to address this limitation. Unlike the standard DEA model, the dynamic DEA model considers carry-over activities as links connecting consecutive periods (Tone and Tsutsui, 2010). These carry-over activities are represented by quasi-fixed inputs, which take longer to adjust. For instance, in airline operations, resource allocation for fleet size and capital stocks serves as carry-over activities between terms, exhibiting lagged effects while maintaining output consistency, aligning with dynamic factors' intermediate nature (Cui and Li, 2017b). These activities reflect an airline's production scale in one term and directly impact efficiency in the next term (Yu and Nguyen, 2023). Consequently, the dynamic DEA model offers more accurate insights when analysing airline performance over a period. The dynamic DEA model has been further developed and applied in various studies on airline efficiency changes. Cui and Li (2017b) analysed the efficiency changes of 19 airlines from 2009 to 2014, using a dynamic epsilon-based model with capital stock as the carry-over activity. Their analysis revealed that the most significant efficiency change occurred in 2010, coinciding with the 2008 financial crisis. Interestingly, different orientations in their DEA models, did not notably influence the efficiency results. Some studies have also used fleet size as the dynamic factor in the DEA model (Cui and Li, 2017a; Li et al., 2016).

2.2.4. Dynamic network DEA model

The network DEA model examines internal DMU relations, while the dynamic DEA model considers intertemporal effects via carry-over activities. Tone and Tsutsui (2014) merged these models, creating a dynamic network DEA model with a slacks-based measure (DNSBM) to evaluate 21 US electric power companies over five years. Compared to the dynamic DEA model with slacks-based measure (DSBM), DNSBM better identifies inefficiencies due to its DMU internal relations consideration. However, DNSBM has drawbacks, as it cannot assess sub-stage efficiency or requires subjective weight specification for sub-stages. To address this, Omrani and Soltanzadeh (2016) proposed a relational dynamic network DEA model (DNDEA), based on models by Kao (2013) and Kao (2013). In their relational model, the same multipliers apply to factors, irrespective of sub-processes, explicitly identifying inefficiency sources. Omrani and Soltanzadeh (2016) particularly used a two-stage DNDEA model to assess eight Iranian airlines in 2010–2012, incorporating dynamic flow with fleet seats. This model computes overall DMU efficiency and tracks dynamic sub-process and period efficiency changes, better serving airlines' performance evaluation needs and revealing inefficiencies.

Several studies have employed dynamic network structures to assess airline performance. Yu et al. (2017) used the DNSBM model to evaluate 30 airlines from 2009 to 2012. They examined the impact of airline alliances and sizes on operational performance. Their network structure comprised production, service, and operations divisions. Results demonstrated a decline in operational efficiency between 2009 and 2012, attributed to the 2008 financial crisis. Losa et al. (2020) also employed the DNSBM model, employing a three-stage network framework (operations, services, and sales) to analyze 22 major international airlines between Annex 1 and non-Annex 1 countries from 2010 to 2016. They found that Annex 1 country airlines outperformed in overall, operations, and service efficiency, but sales performance was inefficient in many Annex 1 countries. Yu and Nguyen (2023) developed an MPI using the DNDEA model to monitor productivity changes in Asia-Pacific airlines during 2017–2019. Their network structure included producing and selling stages with carry-over activities between consecutive years. Results revealed varying productivity changes across airlines, with some improvement due to technological innovation and adaptability, while others showed inefficiency likely due to underutilized resources.

3. Methodology

3.1. Theoretical model

The relational DNDEA model, introduced by Omrani and Soltanzadeh (2016), is utilised in this study for airline evaluation. As illustrated in Fig. 1, the system for evaluation is decomposed to S different internal stages, connected by intermediate products. Carry-over activities flow over T periods, where N and T represents the total number of DMUs and periods, respectively. The variables involved are assumed as follows:

- **Inputs**: $X_{ij}^{(t,s)}$ $(i = 1, \ldots, \mathrm{K}_s, \ldots K, j = 1, \ldots, N, t = 1, \ldots, T, s = 1, \ldots, S)$: denoting the ith input of the jth DMU in period t at stage s, where K_s is the total number of inputs at stage s *and* $i^k \in \{1, \ldots, K_s\}$;
- **Outputs**: $Y_{rj}^{(t,s)}$ $(r = 1, \ldots, R_s, \ldots R, j = 1, \ldots, N, t = 1, \ldots, T, s = 1, \ldots, S)$: denoting the rth output of the jth DMU in period t at stage s, where R_s is the total number of outputs at stage s and $r^k \in \{1, \ldots, R_s\}$;
- **Intermediate products:** $Z_{dj}^{(t,s)}$ $(d = 1, \ldots, D_S, \ldots D, j = 1, \ldots, N, t = 1, \ldots, T, s = 1, \ldots, S)$: denoting the dth intermediate product of the jth DMU in period t and connecting stage s with the subsequent stage and $d^k \in \{1, \ldots, D_s\}$;
- **Carry-overs**: $C_{lj}^{(t,s)}$ $(l = 1, \ldots, L_s, \ldots L, j = 1, \ldots, N, t = 1, \ldots, T-1, s = 1, \ldots, S)$: denoting the lth carry-over of the jth DMU at stage s flowing from period t to period $t+1$, and $l^k \in \{1, \ldots, L_s\}$;

Additionally, the aggregated inputs and outputs are denoted as $X_{ij} = \sum_{t=1}^{T}\sum_{s=1}^{S} X_{ij}^{(t,s)}$ and $Y_{ij} = \sum_{t=1}^{T}\sum_{s=1}^{S} Y_{ij}^{(t,s)}$, respectively.

The choice of orientation can affect the outcomes of the model, and thereby it should be decided in alignment with the specific aim of the analysis (Cook et al., 2014). In the context of this study, management of airline companies might give more focus on the adjustment of their resources, such as operating expenses and service capacity, to cope with the falling travel demand. Therefore, using an input-oriented model is more reasonable. The objective function in the input-oriented form for the overall efficiency, using the relational DNDEA model proposed by Omrani and Soltanzadeh (2016), is presented for the jth DMU under the returns-to-scale assumption as follows:

Model (1):

$$E_j^{sys} = \max\left(\sum_{r=1}^{R_s} u_r Y_{rj} + \sum_{s=1}^{S}\sum_{l=1}^{L} f_l C_{lj}^{(T,s)}\right) \tag{1}$$

Subject to:

$$\sum_{i=1}^{K} v_i X_{ij} + \sum_{s=1}^{S}\sum_{l=1}^{L} f_l C_{lj}^{(t_0,s)} = 1 \tag{2}$$

$$\sum_{r=1}^{R} u_r Y_{rj} + \sum_{s=1}^{S}\sum_{l=1}^{L} f_l C_{lj}^{(T,s)} - \left(\sum_{i=1}^{K_s} v_i X_{ij} + \sum_{s=1}^{S}\sum_{l=1}^{L} f_l C_{lj}^{(t_0,s)}\right) \leq 0, j = 1, \ldots, N \tag{3}$$

Stage 1:

$$\sum_{r\in r^1} u_r Y_{rj}^{(t,1)} + \sum_{d\in d^1} \omega_d Z_{dj}^{(t,1)} + \sum_{l\in l^1} f_l C_{lj}^{(t,1)} - \left(\sum_{i\in i^1} v_i X_{ij}^{(t,1)} + \sum_{l\in l^1} f_l C_{lj}^{(t-1,1)}\right) \leq 0, j = 1, \ldots, N; t = 1, \ldots, T \tag{4}$$

Stage 2 to S-1:

$$\sum_{r\in r^s} u_r Y_{rj}^{(t,s)} + \sum_{d\in d^s} \omega_d Z_{dj}^{(t,s)} + \sum_{l\in l^s} f_l C_{lj}^{(t,s)} - \left(\sum_{i\in i^s} v_i X_{ij}^{(t,s)} + \sum_{d\in d^s} \omega_d Z_{dj}^{(t,s-1)} + \sum_{l\in l^s} f_l C_{lj}^{(t-1,s)}\right) \leq 0, j = 1, \ldots, N; t = 1, \ldots, T; s = 2, \ldots, S-1 \tag{5}$$

Stage S:

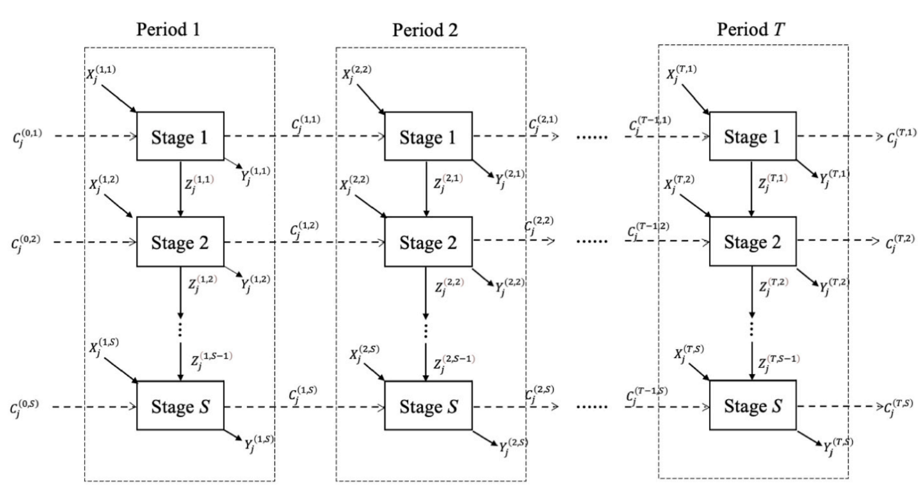

Fig. 1. Dynamic network DEA model with multiple stages and carry-overs.

$$\sum_{r\in r^S} u_r Y_{rj}^{(t,S)} + \sum_{d\in d^S} \omega_d Z_{dj}^{(t,S)} + \sum_{l\in l^S} f_l C_{lj}^{(t,S)} - \left(\sum_{i\in i^S} v_i X_{ij}^{(t,S)} + \sum_{d\in d^S} \omega_d Z_{dj}^{(t,S-1)} + \sum_{l\in l^S} f_l C_{lj}^{(t-1,S)} \right) \leq 0, j = 1,\ldots,N;\ t = 1,\ldots,T \tag{6}$$

$$v_i, u_r, \omega_d, f_l \geq \varepsilon, i = 1,\ldots,K;\ r = 1,\ldots,R;\ d = 1,\ldots,D;\ l = 1,\ldots L \tag{7}$$

where v_i, u_r, ω_d, f_l are the multipliers of input, output, intermediate product, and carry-over, respectively. In addition, $C_{lj}^{(t_0,s)}$ is initial carry-over entering stage s in the first period, and $C_{lj}^{(T,s)}$ is the carry-over flowing out in the last period T.

By solving model (1), the optimal virtual multipliers, denoted as v_i^*, u_r^*, ω_d^*, f_l^* are obtained. Moreover, the efficiency scores of the entire system, denoted as E_j^{sys}, as well as the efficiencies for each period $E_j^{(t,sys)}$, and different stages $E_j^{(t,1)}$ and $E_j^{(t,s)}$, within the system can be calculated. The corresponding equations for the jth DMU are represented by (8)–(11) as follows:

$$\boldsymbol{E_j^{sys}} = \frac{\sum_{r=1}^{R} \boldsymbol{u_r^* Y_{rj}} + \sum_{s=1}^{S}\sum_{l=1}^{L} \boldsymbol{f_l^* C_{lj}^{(T,s)}}}{\sum_{i=1}^{K} \boldsymbol{v_i^* X_{ij}} + \sum_{s=1}^{S}\sum_{l=1}^{L} \boldsymbol{f_l^* C_{lj}^{(t_0,s)}}} \tag{8}$$

$$E_j^{(t,sys)} = \frac{\sum_{s=1}^{S}\sum_{r=1}^{R} u_r^* Y_{rj}^{(t,s)} + \sum_{s=1}^{S}\sum_{l=1}^{L} f_l^* C_{lj}^{(t,s)}}{\sum_{s=1}^{S}\sum_{i=1}^{K} v_i^* X_{ij}^{(t,s)} + \sum_{s=1}^{S}\sum_{l=1}^{L} f_l^* C_{lj}^{(t-1,s)}} \tag{9}$$

$$E_j^{(t,1)} = \frac{\sum_{r\in r^1} u_r^* Y_{rj}^{(t,1)} + \sum_{d\in d^1} \omega_d^* Z_{dj}^{(t,1)} + \sum_{l\in l^1} f_l^* C_{lj}^{(t,1)}}{\sum_{i\in i^1} v_i^* X_{ij}^{(t,1)} + \sum_{l\in l^1} f_l^* C_{lj}^{(t-1,1)}} \tag{10}$$

$$E_j^{(t,s)} = \frac{\sum_{r\in r^s} u_r^* Y_{rj}^{(t,s)} + \sum_{d\in d^s} \omega_d^* Z_{dj}^{(t,s)} + \sum_{l\in l^s} f_l^* C_{lj}^{(t,s)}}{\sum_{i\in i^s} v_i^* X_{ij}^{(t,s)} + + \sum_{d\in d^s} \omega_d^* Z_{dj}^{(t,s-1)} \sum_{l\in l^s} f_l^* C_{lj}^{(t-1,s)}} \tag{11}$$

3.2. Empirical model and variable selection

This study builds an empirical model, drawing from established frameworks and variable selection methods (as outlined in Table 2). The goal is to evaluate airline efficiency dynamically, considering operational, service, financial, and environmental dimensions. This model is adapted from Mallikarjun's (2015) network structure, which segments airline production into operations, service, and sales stages. To account for environmental impact, the model includes an environmental variable as an undesirable output in the service stage.

3.2.1. Operational stage

The initial stage begins with the operational phase, where airlines utilize resources such as aircraft, staff, and aviation fuels to create service capacity for passenger or cargo transportation. Efficient operations enable airlines to maximize service capacity while working within resource constraints, meeting passenger travel demands. As shown in Table 2, operational performance is typically assessed using inputs such as operating expenses, employee count, and fuel consumption. Consequently, one of the operational stage inputs in this study is represented by operating expenses, encompassing costs related to aviation fuel, employee salaries, aircraft maintenance, and other miscellaneous expenses (Mallikarjun, 2015). These expenditures contribute to an airline's ability to produce overall passenger transportation capacity, measured using the Available Seats Kilometres (ASK) metric. ASK represents the total flight seats available multiplied by the cumulative distance they have travelled, commonly used to evaluate operational performance in all airlines (Yu and Nguyen, 2023). Furthermore, operational expenses include employee costs, reflecting the number of airline employees within a given year.

Additionally, Fleet Size (FS) acts as a dynamic factor within the operational stage, connecting two consecutive periods. It indicates the total count of available aircraft, including both owned and leased ones. Unlike other input variables, the fleet size is quasi-fixed, carrying over to the next period and contributing to future production processes (Yu and Nguyen, 2023). For example, airlines may expand their FS based on projected increases in future air travel demand to enhance efficiency. Conversely, if demand forecasts indicate a decline, airlines might reduce FS by cancelling aircraft orders or selling existing aircraft to manage cash flow.

3.2.2. Service stage

In the service stage, the primary goal is to efficiently utilize an airline's available seat capacity and workforce to meet passenger travel demand. Efficiency in this stage enables airlines to maximize passenger traffic while staying within their designated service capacity. Both the ASK and the number of employees can serve as inputs for this stage. Additionally, since they also act as outputs from the previous operational stage, they serve as intermediate products connecting the operational and service stages. Consequently, the total number of passengers transported in a given year is used as one of the outputs. Another output is measured by the Revenue Passenger Kilometres (RPK), reflecting the actual passenger traffic served by an airline (Li et al., 2016). It is calculated by summing the product of paying passengers and the distance they travelled. Furthermore, the Load Factor, representing the utilisation rate of flight seat capacity, serves as another output. This metric is chosen because a higher Load Factor can signify more efficient resource utilisation and improved profitability. This stage significantly contributes to greenhouse gas emissions (GHG) due to aviation fuel combustion during flight operations (Wang et al., 2017). Given the strong correlation between GHG and service efficiency, GHG is considered an undesirable output at this stage. An effective approach to handling undesirable outputs is to treat them as inputs in the model (Li et al., 2016).

3.2.3. Financial stage

The final stage pertains to the financial aspect, which is crucial for an airline's revenue generation. An efficient financial process optimises revenue when the services supplied are certain. Hence, RPK and load factor can be treated as intermediate products, connecting the service and financial stages. Meanwhile, RPK directly influences the financial performance as it is the main determinant of revenue. The total revenue generated by these financial activities is considered as the output for this stage.

The empirical model with dynamic network structure for airline performance evaluation is illustrated in Fig. 2. The inputs, outputs, intermediate produces, and carry-overs are summarised in Table 3.

3.3. Data collection

This empirical study assesses the efficiency of 26 global airlines during the period from 2019 to 2022. This timeframe was chosen because the COVID-19 pandemic emerged by the end of 2019, significantly impacting global travel and the airline industry. To mitigate losses, many airlines implemented efficiency-enhancing measures, such as reducing staff, flight schedules, and cancelling aircraft orders. By 2022, with gradual easing of travel restrictions, international travel patterns began to recover. To understand the pandemic's impact on airline efficiency, data from 2019 to 2022 must be analysed. Furthermore, since the evaluation considers both internal network structures and intertemporal dynamics in airline production processes, data collection must include the initial carry-over from 2018. The dataset

Table 2
Details of studies using DEA to assess airline efficiency.

Author(s)	Samples	Method	Inputs	Intermediate products	Outputs	Key outcomes
Arjomandi and Seufert (2014)	48 full-service and low-cost airlines, 2007–2010	Bootstrapped DEA	• Labour • Capital	N/A	• Available ton km • CO2-e emissions	• China and North Asia airlines excel in technical efficiency, while European carriers lead in environmental performance • Low-cost carriers demonstrate higher environmental orientation and often operate under increasing returns to scale, unlike larger airlines
Choi et al. (2015)	12 US-based airlines, 2008–2011	Service quality-adjusted DEA	• Number of employees • Available seat miles	N/A	• Revenue passenger miles • Operating revenue • Service quality index	• Service quality-adjusted DEA reveals US-based airlines can achieve both quality and productivity without traditional trade-offs • Low-cost carriers benefit from slight service improvements, while network carriers struggle to meet service expectations; long-term focus on service quality enhances customer satisfaction and organizational performance
Schefczyk (1993)	15 large international airlines, 1990	Standard DEA	• Available ton km • Operating cost • Nonflight assets	N/A	• Revenue passenger km • Non-passenger revenue	• Utilizes DEA to analyze and compare operational performance of 15 airlines, concluding with insights into strategic factors contributing to high profitability and performance in the industry
Zhu (2011)	21 airlines, 2007–2008	Two-stage network DEA	• Cost per available seat mile • Salaries per available seat mile • Wages per available seat mile	• Load factor • Fleet size	• Revenue passenger miles • Passenger revenue	• Introduces a two-stage process for measuring airline performance, considering resource allocation and revenue generation simultaneously
Mallikarjun (2015)	27 US airlines, 2012	Three-stage unoriented network DEA	• Operating expenses	1st - 2nd stage: • Available seat miles 2nd - 3rd stage: • Revenue passenger miles	• Operating revenue	• Finds major US airlines are more efficient in operating expenses and revenue generation compared to national US airlines, but no significant difference in service supply and demand efficiencies
Li et al. (2016)	22 airlines, 2008–2012	Three-stage network slacks-based DEA	1st stage: • Number of Employees • Aviation Kerosene 2nd stage: • Fleet size 3rd stage: • Sales cost	1st - 2nd stage: • Available seat km • Available ton km 2nd - 3rd stage: • Revenue passenger km • Revenue ton km	2nd stage: • Greenhouse gas emission (undesirable) 3rd stage: • Total Business Income	• Establishes two models to evaluate efficiencies of 22 international airlines from 2008 to 2012, showing increased efficiencies over the period, higher average efficiency for European airlines, and differentiating efficacy between weak disposability and strong disposability models
Cui and Li (2017c)	29 airlines, 2008–2015	Dynamic by-product DEA model	•Number of employees •Aviation Kerosene	Carry-over: •Fleet Size	•Total Revenue •Greenhouse gas emission (undesirable)	•Analyzes the impact of the "Carbon Neutral Growth from 2020" (CNG2020) strategy on airline efficiency using predicted data of 29 international airlines from 2021 to 2023
Cui and Li (2017b)	19 airlines, 2009–2014	Dynamic DEA with Epsilon-Based Measure	• Number of employees • Aviation Kerosene	Carry-over: • Capital stock	• Revenue ton km • Revenue passenger km • Total revenue	• Identifies Scandinavian, Emirates, and Cathay Pacific as benchmarking airlines among 19 studied airlines, with significant efficiency changes observed in 2010 linked to the 2008 financial crisis
Wang et al. (2017)	49 airlines, 2008–2013	Dynamic DEA with slacks-based measure	• Operating expenses	Carry-over: • Equities • Liabilities • Intangible assets	• Revenue • Market value	• Finds that asset-light strategy significantly enhances corporate performance, suggesting efficient management and allocation of resources crucial for navigating challenges in the dynamic global airline industry
Omrani and Soltanzadeh (2016)	8 Iranian airlines, 2010–2012	Two-stage dynamic network DEA	• Number of employees	• Available ton km • Available seat km • Number of scheduled flights Carry-over:	• Passenger km perfumed • Ton km perfumed	• Applies proposed model to measure efficiency of eight Iranian airlines across multiple periods from 2010 to 2012, highlighting its capability compared to dynamic DEA and network DEA models, offering insights for operational performance improvement

(continued on next page)

Table 2 (*continued*)

Author(s)	Samples	Method	Inputs	Intermediate products	Outputs	Key outcomes
				• Number of fleet's seat		
Yu et al. (2017)	30 global airlines, 2009–2012	Two-stage dynamic network DEA model with a slacks-based measure	• Size of leased fleet • Labour expenses • Fuel expenses • Other operational expenses	• Available seat km • Freight available ton km Carry-overs: • Size of self-owned fleet • Waypoints	• Revenue passenger km • Freight revenue ton km	• Empirical findings reveal significant impacts of weight setting on operational efficiency, declining trend in overall efficiency, and significant influences of joining airline alliances, total assets, and GDP on operational performance
Losa et al. (2020)	22 airlines, 2010–2016	Three-stage dynamic network DEA model with a slacks-based measure	• Operational expenses • Fleet capital	• Available seat km • Revenue passenger km Carry-overs: • Investment in assets	• Passenger revenue	• Annex 1 airline groups generally perform better in managing overall production processes, operations, and services efficiencies, potentially influenced by the Kyoto Protocol; however, sales efficiency results do not fully support this hypothesis, revealing high inefficiency among some Annex 1 airline groups compared to rivals
Yu and Nguyen (2023)	25 full-service carriers in Asia-Pacific, 2017–2019	Two-stage dynamic network DEA	• Employees • Fuel (tons)	• Available ton km • Freight available ton km Carry-overs: • Total MTOW • Waypoints	• Revenue passenger km • Freight revenue ton km	• Empirical results show diverse efficiency levels and productivity changes, with most airlines demonstrating continuous improvement supported by technology innovation or adaptation, while low resource utilisation emerges as a prominent inefficiency cause, gradually addressed by airlines

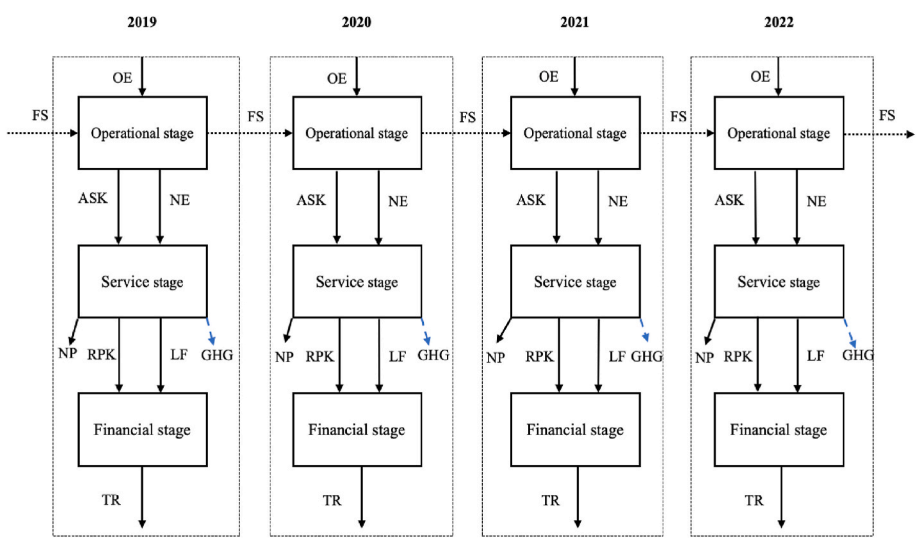

Fig. 2. Empirical structure for airline performance evaluation.

containing inputs, outputs, intermediate products, and carry-over can be found in Appendix A.

The selection of airline samples for this empirical study is based on the airline rankings provided by the International Air Transport Association, which ranked international airlines by the total number of passengers carried (IATA, 2019). Considering data availability for the selected variables, a total of 26 prominent airlines were chosen for data collection from their respective annual reports, sustainability reports, and ESG reports (see Appendix A). These airlines operate internationally and represent regions across Asia, Europe, America, and Oceania. Nevertheless, as the foremost factor in the selection process is the total passenger capacity, it is important to acknowledge that the geographical variations have not been thoroughly accounted for when choosing these airline samples. This omission could potentially result in an analysis that is not easily comparable and represents the primary limitation of utilizing these particular samples.

Among these airlines, six belong to the low-cost carrier (LCC) category, also known as budget airlines (Xu et al., 2023). These include Ryanair, EasyJet, Wizz Air, Norwegian Air Shuttle, IndiGo, and Scoot. LCCs offer relatively lower fares for basic tickets and provide limited services compared to full-service carriers (FSCs). Previous research has shown that during the pandemic, FSCs and LCCs adopted different measures, with LCCs demonstrating more efficiency (Kaffash and Khezrimotlagh, 2023). Therefore, investigating the performance comparison between FSCs and LCCs is of interest.

The data for the operational expenses, fleet size, ASK, number of employees, RTK, load factors, number of passengers, and total revenue are drawn from airlines' annual reports from 2018 to 2022. The GHG data is sourced from the airlines' sustainability reports or ESG reports at this time. Since the operational expenses and total revenue are monetary

Table 3
–Definitions of variables.

Item	Variable	Description
Inputs	Operating expenses (OE)	Expenses incurred in operations, including aviation fuel, employee salaries, aircraft maintenance and other operational costs.
Intermediate products	Available Seats kilometre (ASK)	Overall passenger-carrying capacities, measured in available seats multiplied by the distance travelled.
	Number of employees (NE)	Total number of the employees of an airline in the given period.
	Revenue passenger kilometre (RPK)	The sum of products obtained by multiplying the actual paying passengers by the distance travelled.
	Load factor (LF)	The percentage of available seats filled by passengers on a flight over the given period.
Carry-over	Fleet size (FS)	Total number of aircraft available for service, including own and the leased aircrafts.
Output	Number of Passengers (NP)	Total number passengers transported in the given year.
(desirable)	Total revenue (TR)	The overall income and other operating income generated within the given year
Output (undesirable)	Greenhouse gas emission (GHG)	The gases include CO_2, NO_x, and SO_x, with CO_2 been the most significant GHG. This study mainly considers the direct or scope 1 emissions resulting from combustion of fuels in aircraft, as it is the major source of GHG for an airline.

values and are given in different currencies, they are first converted to the US dollar to be applied in the model with consistency. The descriptive details of these factors are presented in Table 4.

4. Research findings

The findings section has two parts. It starts with an overview of the average trends of variables during the sample period from 2019 to 2022. The second part provides detailed efficiency analysis, including overall and period efficiencies and efficiency of each stage.

4.1. An overview

Overall, the average values of all variables demonstrate a similar pattern (see Fig. 3). In 2019, these averages stood at the highest for all variables, and fell significantly to the lowest point in 2020. This was followed by a gradual rebound in the following years. Nevertheless, as of 2022, these values have not yet fully returned to the pre-pandemic level in 2019. However, based on the level of change, the patterns can be divided into three groups.

In the first group, the values in 2022 were approaching more closely to the pre-pandemic level. For instance, as the input of the initial stage, the operating expenses of the 26 airlines in 2019 stood at $14,601 million on average and then declined by 36.5% to $8932 million in 2020. This could suggest that airlines were responding to the pandemic and taking measures to cut down investment in resources. It then rebounded slightly in 2021, with the value approaching the pre-pandemic level by 2022.

Table 4
Descriptive statistics.

Variable	Mean	Std. dev.	Min	Max
Operating expenses (10^6 USD)	11438.74	10469.73	766.46	47364.00
Available Seats kilometre (10^6)	127039.32	111044.29	2228.20	458803.52
Number of employees	40269.24	33150.99	1747.00	133700.00
Revenue passenger kilometre (10^6)	98078.18	93081.78	221.60	388256.49
Load factor (%)	71.52	16.55	9.90	95.00
Fleet size	430.53	388.80	51.00	1551.00
Number of Passengers (10^6)	50.22	47.73	0.08	199.29
Total revenue (10^{6v}USD)	10926.21	11119.91	212.30	50582.00
Greenhouse gas emission (10^4 tons CO_2 equivalent)	1121.52	935.35	55.60	4114.30

In the second group, the values in 2022 were still significantly lower than the pre-pandemic level. For example, the output of the first stage - ASK reduced by 57% on average in 2020 and reached around 70% of the pre-pandemic level by 2022. Other variables, such as the number of passengers, RPK, and total revenue also exhibited a similar pattern.

In the final group, variables including fleet size and number of employees displayed little change over the sample period. These non-aligned changes between inputs and outputs imply the potential for inefficiencies within airlines' production processes. In addition, it is imperative to recognise that the aforementioned observations stem solely from the average values of 26 airlines. Considering the diverse performance among different airlines, it is necessary to further explore airlines efficiency changes under the impact of the pandemic and identify the source of inefficiency.

To examine the relation among inputs and outputs, as well as carry-over and intermediate products, which also can be viewed as the input or output for sub-stages, the Pearson correlation analysis is performed (Cohen et al., 2009), with the results of coefficients shown in Table 5. Overall, the coefficients between inputs and outputs are high and positive.

For instance, in the operational stage, a robust correlation is evident between the input variable "Operating Expense" and the output variables "ASK" as well as "Number of Employees", with coefficients of 0.924 and 0.823, respectively. In the following service stage, the input variable "ASK" and the output variable "RPK" also display a significant correlation (0.987). In the financial stage, the coefficient between "RPK" and "Total Revenue" stands at 0.931. Moreover, when viewing this system holistically, the input variable "Operating Expense" and the output variable "Total Revenue" suggest a notable correlation of 0.973. These coefficients highlight the fact that a higher output generation is likely to correspond with an increased level of input. Given these results, the closely correlated relation between the inputs and outputs, as incorporated in this empirical dynamic network DEA model, is verified. Consequently, the selection of inputs and outputs can be justified (Cui and Li, 2017a).

4.2. Empirical results of efficiency analysis

4.2.1. Overall and period efficiencies

By applying the airline dataset to the empirical dynamic network DEA model (1) in Section 3, the optimal weights for variables of each airline can be derived. Then, using equations (8) and (9), the overall system efficiency scores, along with the yearly efficiency scores for individual airlines, are obtained and presented in Table 6.

In general, the average overall efficiency score is only 0.838, suggesting that the performance of the airline industry is not highly efficient over these four years. Notably, none of these airlines achieved full efficiency, as their system efficiency scores all fall short of 1. Among the 26 airlines, China Southern Airlines, Turkish Airlines, and Qantas Airway rank in the top three positions, with efficiency scores of 0.978, 0.964, and 0.963, respectively. Despite their top positions, they are still below full efficiency. In contrast, Cathay Pacific Airways, Norwegian Air Shuttle, and IndiGo exhibit the lowest system efficiency scores, which are 0.530, 0.643, and 0.694. In addition, as illustrated through the boxplot in Fig. 4, more than half of the DMUs' system efficiency scores are below 0.9, indicating the suboptimal efficiency for most airlines during the sample period.

In terms of the yearly efficiency, the average score peaks at 0.958 in 2019, and then drops to a nadir of 0.862 in 2020. This could be

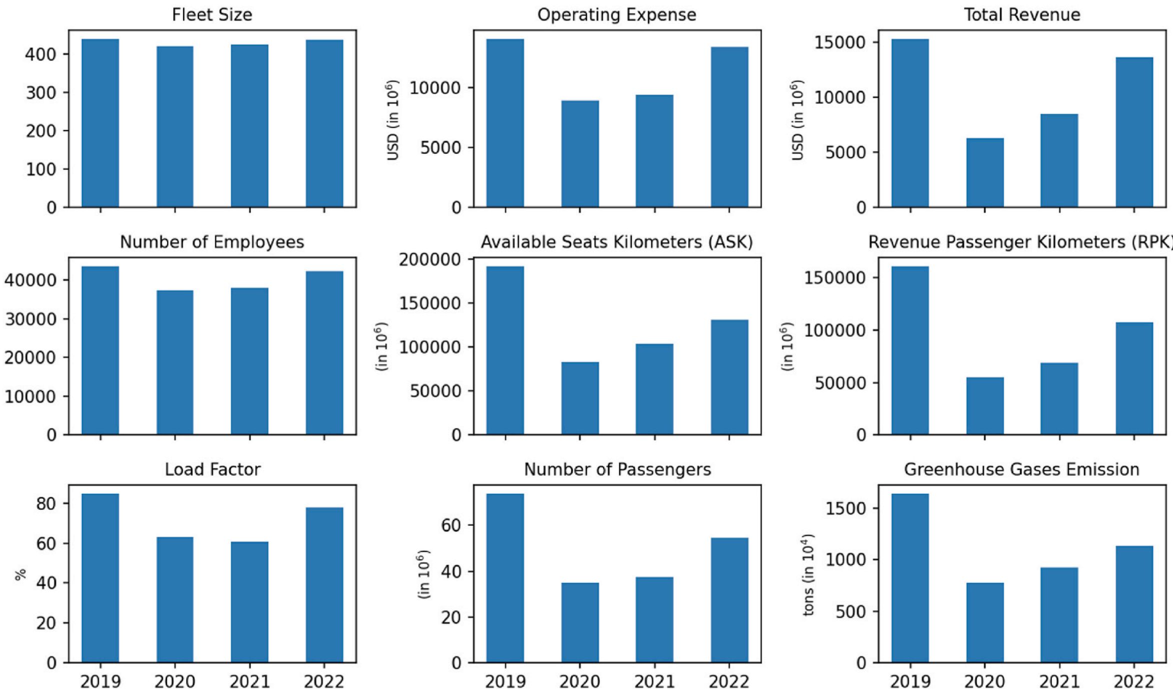

Fig. 3. Average values of variables during 2019–2022.

Table 5
Pearson correlation coefficients among variables.

	Operating Expense	ASK	Number of Employees	RPK	Load Factor	Number of Passengers	GHG	Total Revenue	Fleet Size
Operating Expense	1.000								
ASK	0.924	1.000							
Number of Employees	0.823	0.802	1.000						
RPK	0.896	0.987	0.744	1.000					
Load Factor	0.217	0.387	0.126	0.455	1.000				
Number of Passengers	0.728	0.850	0.690	0.863	0.457	1.000			
GHG	0.926	0.962	0.812	0.947	0.303	0.756	1.000		
Total Revenue	0.973	0.934	0.749	0.931	0.292	0.747	0.935	1.000	
Fleet Size	0.857	0.814	0.872	0.751	0.127	0.751	0.761	0.767	1.000

intricately linked with the outbreak of the pandemic, which significantly disrupted airlines' production process. However, as airlines took measures to cut down expenses and travel demand began to recover in 2021, the efficiencies saw an improvement, rising to 0.916 in 2021 and further increasing to 0.938 in 2022.

Before the pandemic, in 2019, both China Southern Airlines and China Eastern Airlines achieved an efficiency score of 1, which means that their system performance was considered fully efficient. Besides, as can be seen from the boxplot in Fig. 4, the majority of airlines exhibited high efficiency scores, closing to 1. Only a few outliers exhibited much lower efficiency, such as Cathay Pacific Airways, which also ranks at the bottom in terms of overall efficiency. However, in 2020, none of the airlines attained full efficiency. Except for Turkish Airlines and EasyJet, all the other airlines exhibited relatively poorer performance compared to the previous year. The drop in efficiency is particularly noticeable for Norwegian Air Shuttle, from 0.996 in 2019 to 0.335 in 2020. Although the efficiency increased slightly in the next two years, its rank remained at the bottom position. In 2021, most airlines had seen an increase in efficiency. Emirates achieved full efficiency, and American Airlines and United Airlines were almost fully efficient (0.999). By 2022, the system efficiency levels have rebounded, approximating the level of the year 2019. Furthermore, China Southern Airlines had returned to the top position again in the ranking. Several potential factors may contribute to the observed efficiency results. Upon a detailed analysis of the data presented in Appendix A, it is evident that China Southern Airlines experienced a significant decline in the total number of passengers carried from 2019 to 2022. Notably, the decline persisted from 2021 to 2022 at a rate of 36.4%, which is in contrast to the recovery trend observed in many other airlines examined in the study. The pattern is similar for other variables such as ASK, RPK, and GHG. While the total revenue followed the declining trend from 2019 to 2020, it exhibited only marginal fluctuations thereafter, with a mere 18% fall from 2021 to 2022. As gleaned from the annual report, this can be attributed to the increase of non-domestic passenger numbers despite significant fall in domestic passengers (China Southern Airlines, 2023). Compared to less efficient airlines like Cathay Pacific Airways, it is noticeable that while its passenger numbers nearly tripled in 2022, the total revenue only saw a slight increase, which might affect its efficiency.

It is worth noting that, except for EasyJet, most LCCs consistently displayed lower annual efficiency scores compared with FSCs throughout the study period. This finding aligns with the study by Choi (2017). Moreover, it appears that LCCs were more profoundly affected by the pandemic and recovered slower than their FSC counterparts. This is evident from their persistent bottom-ranking positions after 2019.

A regression analysis was conducted to statistically evaluate the impact of the pandemic on efficiency scores. This analysis focused on efficiency scores at each stage as well as the overall system. The study's timeframe included a short pre-pandemic period in 2019 and a longer post-pandemic period spanning from 2020 to 2023. To achieve more balanced and accurate results, only data from 2019 to 2020 were used in

Table 6
Overall and periodical system efficiencies during 2019–2022.

DMU	Type	Overall	Rank	2019	Rank	2020	Rank	2021	Rank	2022	Rank
Ryanair	LCC	0.876	12	0.953	20	0.612	24	0.783	24	0.958	14
EasyJet	LCC	0.884	9	0.997	10	0.997	2	0.884	19	0.994	6
Emirates	FSC	0.915	8	0.984	16	0.951	10	1.000	1	0.975	10
Lufthansa	FSC	0.850	16	0.972	17	0.965	8	0.839	21	0.927	21
British Airways	FSC	0.843	17	0.998	6	0.890	17	0.975	14	0.965	13
Turkish Airlines	FSC	0.964	2	0.987	15	0.998	1	0.974	15	0.997	4
KLM	FSC	0.868	13	0.994	13	0.902	15	0.920	18	0.971	12
Wizz Air	LCC	0.880	11	0.948	21	0.932	11	0.966	16	0.997	3
Norwegian Air Shuttle	LCC	0.643	25	0.996	12	0.335	26	0.390	26	0.522	26
American Airlines	FSC	0.854	15	0.968	18	0.887	18	0.999	3	0.985	9
United Airlines	FSC	0.828	18	0.959	19	0.914	14	0.999	4	0.930	20
Delta Airlines	FSC	0.737	21	0.940	22	0.767	22	0.998	5	0.972	11
Cathay Pacific Airways	FSC	0.530	26	0.647	26	0.984	5	0.821	23	0.838	25
Singapore Airlines	FSC	0.782	20	0.886	24	0.884	19	0.997	7	0.953	16
Scoot	LCC	0.697	23	0.929	23	0.767	21	0.997	6	0.911	22
Korean Air	FSC	0.882	10	0.999	5	0.930	12	0.957	17	0.990	7
Iberia	FSC	0.728	22	0.760	25	0.468	25	0.851	20	0.996	5
Scandinavian Airlines	FSC	0.854	14	0.998	8	0.683	23	0.720	25	0.896	23
China Southern Airlines	FSC	0.978	1	1.000	1	0.987	4	0.992	9	0.998	1
China Eastern Airlines	FSC	0.943	5	1.000	2	0.963	9	0.987	11	0.987	8
Air China	FSC	0.942	6	0.999	3	0.968	7	0.996	8	0.953	15
LATAM Airlines	FSC	0.798	19	0.998	9	0.843	20	0.985	12	0.943	17
IndiGo	LCC	0.694	24	0.990	14	0.900	16	0.826	22	0.867	24
Qantas airway	FSC	0.963	3	0.999	4	0.968	6	0.983	13	0.998	2
Finnair	FSC	0.919	7	0.998	7	0.987	3	0.999	2	0.933	19
Hainan Airline	FSC	0.946	4	0.997	11	0.930	13	0.989	10	0.941	18
Average		0.838		0.958		0.862		0.916		0.938	

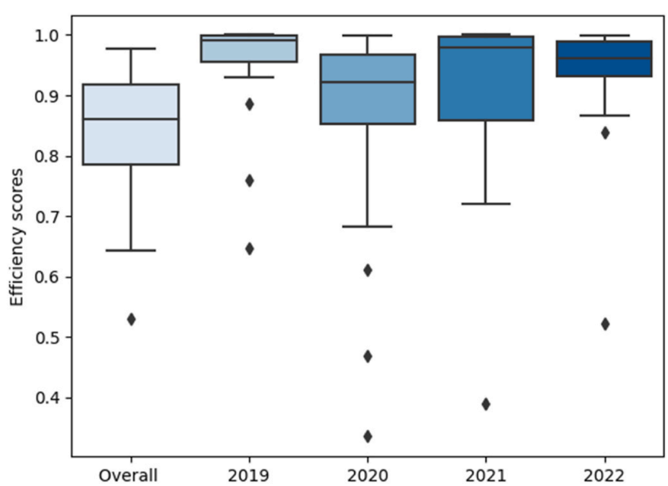

Fig. 4. Distribution of overall and yearly system efficiency scores.

the regression model. The regression model was formulated as described in Yu et al. (2019):

$$\text{Eff\_score}_{it} = \delta_0 + \beta_1 \text{ Pandemic}_{it} + \varepsilon_{it},$$

where δ_0 denotes the intercept; ε_{it} is the residual; Eff_score_{it} represents the efficiency scores of each stage and the overall system for airline i in year t; Pandemic_{it} is a dummy variable that equals unity if year t is within the pandemic period, and β represents its coefficient.

The regression results in Table 7 showcase the relationship between efficiency scores at different stages and the overall system efficiency, particularly in relation to the pandemic period. The regression coefficients reveal a negative correlation between the pandemic period and airline efficiency scores across all stages and the overall system efficiency. Notably, the statistical significance of the pandemic's association is evident in stages 1 and 2, indicating significant impacts of the pandemic on airline efficiencies during these stages.

Table 7
Regression results of the DEA efficiency scores.

Coefficients	Stage 1 Efficiency	Stage 2 Efficiency	Stage 3 Efficiency	System Efficiency
Pandemic Period	−0.057[a]	−0.108[a]	−0.033	−0.015
	(0.022)	(0.053)	(0.049)	(0.022)
Intercept	0.972[b]	0.914[b]	0.847[b]	0.940[b]
	(0.015)	(0.037)	(0.035)	(0.015)
No. Samples	52	52	52	52

Note: Standard errors are presented in parentheses.
[a] $p < 0.05$.
[b] $p < 0.01$.

4.2.2. Efficiency of each stage

Using the optimal weights and formulae given in (10) and (11), the efficiency scores for three stages from 2019 to 2022 are computed and presented in 8. When comparing the yearly averages for each stage, it is found that the performance of the first stage - operational stage is generally stable and efficient, with mean values consistently above 0.9. In stage 2, there is an evident decline in performance from 2019, reaching relatively low levels in 2020 and 2021, with average scores of 0.806 and 0.781, respectively. This suggests that the airlines might not have adjusted their resource allocation effectively in keeping up with the falling passenger demand during these years. An alternative perspective posits that airlines may have been constrained in reducing resource allocation below a certain threshold due to substantial fixed costs, particularly related to fleet size. Stage 3 exhibited relatively lower efficiency on average in 2019 and 2020, with scores of 0.847 and 0.813, respectively. However, there has been an improvement in the subsequent two years, indicating efforts to enhance financial efficiency.

To have an explicit understanding of the results of individual airlines, the distribution of the efficiency scores of three stages during 2019–2022 is depicted by a boxplot in Fig. 5. As shown, stage 1 generally exhibits the high efficiency. Despite some fluctuation in efficiency over the study period, the distributions remain relatively concentrated and close to 1, signifying operational stability and adaptability. Conversely, the distribution of efficiency scores for stage 2 - service stage is scattered from 2019 to 2021. However, in 2022, the

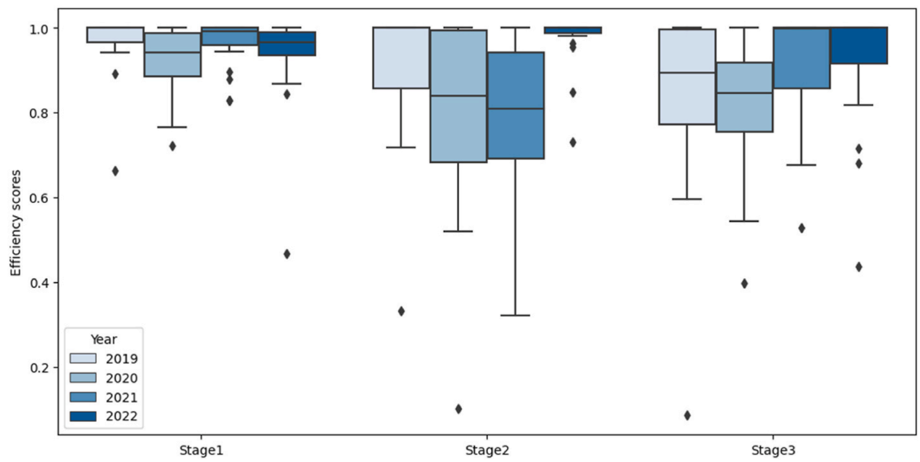

Fig. 5. Distribution of stage efficiency scores during 2019–2022.

efficiencies in stage 2 of most of the airlines were improved significantly and approached full efficiency. The financial performance in stage 3 exhibits enhancement after the pandemic, with the distribution becoming even more concentrated in 2022, implying higher efficiency compared to the 2019 level. The change of distributions in stages 2 and 3 indicates that the sources of inefficiency are primarily located in these two stages. Consequently, airlines may benefit from dedicating their improvement efforts to service and financial aspects against unexpected crises.

5. Discussions

This section analyses the obtained results from the theoretical and managerial perspectives and discusses the implications extracted from the analyses. From the results and the corresponding discussion presented in the sequel, we first verify the proposed model's robustness and theoretical superiority. In addition, the managerial implications supported by empirical evidence result in several crucial suggestions on recovering and further improving the performance of airlines in the face of global crises in the future.

5.1. *Theoretical implications*

This study mainly contributes to exploring the impact of the COVID-19 pandemic on global airlines' performance from the operational, service, environment, and financial perspective via a novel DEA method. So far, to the author's best knowledge, no existing literature has applied the three-stage dynamic network DEA approach in examining the efficiency changes of global in the context of the COVID-19 pandemic. Only a few studies have used different models in examining the impact in the context of the pandemic. Kaffash and Khezrimotlagh, (2023) studied the impact of the COVID pandemic on the performance of nine US airlines. In this study, the performance of 2019 and 2020 was evaluated individually through a two-stage network DEA method without considering the dynamic flow in two consecutive years. Similarly, a decrease in efficiency from 2019 to 2020 is observed in the results. However, the finding on the performance of LCCs and FSCs is opposite, showing that LCCs have higher efficiency than that of FSCs. The opposite results could be attributed to the different empirical models, the region, and the number of airlines studied in the research. Also, despite the internal structure considered in the model, the author of the existing work did not make good use of the model to further explore the efficiency of each stage.

As discussed in Section 2, the network structure in the DNDEA model allows the system to be viewed as several connected processes, instead of a black box with only aggregated inputs and outputs. Consequently, the scores obtained for each stage can help identify the processes with relatively low efficiency in the system and provide more insights. For instance, Table 8 shows that most airlines have high efficiency at the operational stage, i.e., stage 1, when compared to that of another two stages. Besides, despite the impact of the pandemic, the operational efficiency only sees slight fluctuation and always stays above 0.9. In contrast, the efficiencies in stages 2 and 3, i.e., the service and financial stages, have more obvious fluctuations over the sample period. Especially in 2020, the efficiency suffers from a severe decrease. These results indicate that the adjustment in the service and financial stages should be given more attention, to improve the overall efficiency during the crisis.

Moreover, in comparison to the traditional static DEA model, the DDEA model offers better accuracy in estimating the dynamic efficiency by incorporating the inter-temporal effect (Kao, 2013). However, the DDEA model does not consider the internal relations among sub-processes. In order to examine the advantages of the DNDEA model employed in this study over the DDEA model, the outcomes are calculated by both models, and the annual efficiency scores are compared in Table 9. The formulation of the DDEA model can be found in Appendix B. The inputs, outputs, and carry-over used in the DDEA model remain the same as those of the empirical model.

The average efficiency scores of each year are displayed in the final column of Table 8. It is evident that the efficiency scores derived from the DDEA model tend to be higher compared to those from the DNDEA model. Especially for the year 2020, the average efficiency score is 0.926 returned by the DDEA model, while the score is 0.862 using the DNDEA model. This shows that the DDEA model does not capture the inefficiency of some DMUs and overestimates their performance. For example, 5 out of 26 airlines are regarded as fully efficient in 2020 when evaluated by the DDEA model, while the number is zero using the DNDEA model. The cause behind the mismatch might be the network structure incorporated in the DNDEA model, and there are more constraints involved in the formulation. Hence, it can be corroborated that the empirical DNDEA model employed in this study is more accurate and exhibits greater discriminatory power in evaluating the dynamic efficiency of airlines across multiple dimensions.

5.2. *Managerial & political implications*

The empirical results obtained from this study can provide several managerial implications, especially for airline managers as well as policymakers in coping with the challenges of airline performance during crises similar to the COVID-19 pandemic.

Firstly, since the sample airlines used for evaluation are major carriers that transport passengers in large volumes, the regional differences are not significant. However, the efficiency scores for 2020 and 2021

Table 8
Efficiencies of three stages for individual airlines from 2019 to 2022.

DMU	Stage 1				Stage2				Stage 3			
	2019	2020	2021	2022	2019	2020	2021	2022	2019	2020	2021	2022
Ryanair	0.964	0.722	1.000	0.968	1.000	0.811	0.861	0.986	0.981	1.000	0.887	1.000
EasyJet	1.000	1.000	0.897	0.996	1.000	1.000	0.321	0.955	0.904	0.779	1.000	1.000
Emirates	0.985	0.952	1.000	0.975	0.899	0.743	0.806	1.000	0.743	0.935	1.000	1.000
Lufthansa	1.000	1.000	0.878	0.925	1.000	0.856	0.804	1.000	0.935	0.910	0.967	1.000
British Airways	1.000	0.890	0.976	0.965	0.844	0.700	0.712	1.000	0.887	0.845	1.000	1.000
Turkish Airlines	1.000	1.000	0.981	0.998	1.000	0.995	0.813	0.981	0.764	0.919	1.000	1.000
KLM	1.000	1.000	0.991	0.970	1.000	0.542	0.598	1.000	0.969	0.911	0.992	1.000
Wizz Air	0.948	0.931	0.967	1.000	0.983	1.000	0.805	0.964	0.958	1.000	1.000	0.824
Norwegian Air Shuttle	1.000	0.956	0.954	0.467	1.000	0.519	0.752	1.000	1.000	0.663	0.528	1.000
American Airlines	0.969	0.887	1.000	0.985	0.941	0.743	0.901	1.000	0.835	0.831	0.815	1.000
United Airlines	0.959	0.915	1.000	0.930	1.000	0.824	0.946	1.000	0.850	0.814	0.824	1.000
Delta Airlines	0.941	0.768	1.000	0.972	1.000	0.676	0.864	1.000	0.765	0.895	0.857	1.000
Cathay Pacific Airways	0.664	1.000	0.828	0.844	0.332	0.559	0.376	1.000	0.903	0.544	1.000	0.436
Singapore Airlines	0.891	0.885	1.000	0.955	0.740	0.564	0.593	1.000	0.626	1.000	0.854	0.716
Scoot	0.943	0.777	1.000	0.912	0.773	0.102	0.493	1.000	0.086	0.748	1.000	0.817
Korean Air	1.000	0.931	0.957	0.990	0.718	0.825	0.563	1.000	0.596	0.549	1.000	0.681
Iberia	1.000	0.777	1.000	1.000	1.000	1.000	0.930	0.995	0.695	0.397	0.858	1.000
Scandinavian Airlines	1.000	0.765	0.945	0.964	1.000	0.923	0.757	1.000	1.000	0.955	1.000	0.927
China Southern Airlines	1.000	0.987	0.992	0.998	1.000	0.963	0.973	1.000	1.000	0.847	1.000	0.980
China Eastern Airlines	1.000	0.963	0.988	0.988	1.000	0.981	0.855	0.992	1.000	0.809	1.000	0.906
Air China	1.000	0.987	1.000	0.959	1.000	0.982	0.960	1.000	1.000	0.840	1.000	0.912
LATAM Airlines	1.000	0.844	0.987	0.942	1.000	1.000	0.953	1.000	0.791	0.674	0.735	1.000
IndiGo	1.000	0.903	0.828	0.867	0.752	0.659	1.000	0.849	0.834	0.850	0.676	1.000
Qantas airway	1.000	0.976	0.992	1.000	0.996	1.000	1.000	0.980	1.000	0.942	0.867	1.000
Finnair	1.000	0.987	1.000	0.933	0.783	1.000	0.684	0.731	0.887	0.632	1.000	1.000
Hainan Airline	1.000	0.982	1.000	0.939	1.000	0.994	0.981	1.000	1.000	0.860	0.996	1.000
Average	0.972	0.915	0.968	0.940	0.914	0.806	0.781	0.978	0.847	0.813	0.918	0.931

Table 9
Annual efficiency scores calculated by different models.

DMU	DNDEA model				DDEA model			
	2019	2020	2021	2022	2019	2020	2021	2022
Ryanair	0.953	0.612	0.783	0.958	0.901	0.989	1.000	0.958
EasyJet	0.997	0.997	0.884	0.994	0.997	1.000	0.885	0.993
Emirates	0.984	0.951	1.000	0.975	0.985	0.952	1.000	0.975
Lufthansa	0.972	0.965	0.839	0.927	0.787	1.000	0.814	0.801
British Airways	0.998	0.890	0.975	0.965	1.000	0.896	0.984	0.977
Turkish Airlines	0.987	0.998	0.974	0.997	0.987	1.000	0.974	0.990
KLM	0.994	0.902	0.920	0.971	1.000	0.919	0.959	0.981
Wizz Air	0.948	0.932	0.966	0.997	0.948	0.931	0.967	1.000
Norwegian Air Shuttle	0.996	0.335	0.390	0.522	0.841	0.765	0.367	1.000
American Airlines	0.968	0.887	0.999	0.985	0.968	0.891	1.000	0.993
United Airlines	0.959	0.914	0.999	0.930	0.956	0.920	1.000	0.939
Delta Airlines	0.940	0.767	0.998	0.972	0.937	0.783	1.000	0.996
Cathay Pacific Airways	0.647	0.984	0.821	0.838	0.664	1.000	0.828	0.844
Singapore Airlines	0.886	0.884	0.997	0.953	0.877	0.905	1.000	0.970
Scoot	0.929	0.767	0.997	0.911	0.943	0.777	1.000	0.912
Korean Air	0.999	0.930	0.957	0.990	1.000	0.931	0.958	0.994
Iberia	0.760	0.468	0.851	0.996	0.899	0.883	0.831	1.000
Scandinavian Airlines	0.998	0.683	0.720	0.896	0.965	0.855	0.908	1.000
China Southern Airlines	1.000	0.987	0.992	0.998	1.000	0.988	0.993	1.000
China Eastern Airlines	1.000	0.963	0.987	0.987	1.000	0.966	0.992	1.000
Air China	0.999	0.968	0.996	0.953	0.955	0.967	1.000	0.975
LATAM Airlines	0.998	0.843	0.985	0.943	1.000	0.852	0.994	0.946
IndiGo	0.990	0.900	0.826	0.867	1.000	1.000	0.871	0.940
Qantas airway	0.999	0.968	0.983	0.998	0.970	0.967	0.987	1.000
Finnair	0.998	0.987	0.999	0.933	0.999	0.987	1.000	0.933
Hainan Airline	0.997	0.930	0.989	0.941	0.788	0.963	1.000	0.998
Average	0.958	0.862	0.916	0.938	0.937	0.926	0.935	0.966

indicate that EasyJet and Wizz Air managed to maintain a relatively stable performance despite the challenges. Conversely, several other LCC airlines, including Ryanair, Norwegian Air Shuttle, IndiGo, and Scoot experienced a noticeable efficiency decline compared to the decrease with other airlines, particularly to both stages 2 and 3. The main driver behind this phenomenon could be the simple business model of LCCs – wherein tickets are sold at low fares to attain high load factors and profitability. Consequently, these budget airlines tend to be more dependent on passenger traffic in high density to sustain their operational and financial health. To mitigate the financial constraints, low-cost airlines should first implement cost-cutting measures to reduce their operating expenses. One of the major expenses is on aviation fuel, which is a common risk factor for airlines' profitability as the market price of crude oil varies in an almost unpredictable manner. The impact of oil price fluctuation is also indicated in the findings. The escalation of the Russo-Ukrainian war in 2022 led to an oil price surge, and this is well reflected by our findings in Table 7 as the average operational efficiency drops from 0.968 in 2021 to 0.94 in 2022. Therefore, airlines must have a more strategic approach to maintaining fuel costs. For example, airlines would have better financial derivatives in hedging fuel prices. In addition, airlines can minimise fuel consumption via the adjustment of service capacity, such as removing routes with less profit or demand.

In 2020, total service capacity was reduced by around 57% according to the data of ASK, and the total passenger numbers reduced by 58.8%. However, the low-efficiency scores at stages 2 and 3, illustrated in Table 7, demonstrate that there is still room for improvement in revenue generation as well as GHG emissions. As discussed above, LCCs have a relatively simple business model of only providing passenger service, including selling flight tickets and other ancillary service, such as checked baggage and seat selection. Conversely, full-service airlines, e.g., Emirates, Lufthansa Airlines, and Turkish Airlines, provide cargo service in addition to their passenger services. During the pandemic, when there was a significant reduction in flight passengers, it is also very important that airlines diversify their business and optimise their revenue structure. For instance, LCCs should also take advantage of the belly of the aircraft and make efficient use of their available capacity to carry cargo.

For environmental efficiency, the GHG data used for calculation is the scope 1 emissions or direct emissions from flight operations, which are mainly related to fuel consumption. As a result, in order to improve environmental performance, airlines should consider modernising their fleet and investing in more fuel-efficient aircraft. Furthermore, there are some renewable fuels, for example, sustainable aviation fuel or biofuel, which can also be considered as alternatives to traditional fossil fuels.

Crises, including but not limited to events like pandemics, are frequent occurrences and are likely to recur, posing ongoing challenges to the aviation industry. Consequently, policymakers can learn valuable lessons from these experiences and implement a range of measures to support airlines in overcoming these challenges and enhancing their efficiencies. In the short term, when such a crisis takes place, governments can offer tax reduction or relief measures to alleviate airlines' operating cost, such as airport fees, landing charges, and other related taxes. In addition, to support airlines, financial bailouts should be extended to airlines to ensure the continuity of their operations, maintain the cash flow, and prevent bankruptcies. Furthermore, given the rapidly changing nature of pandemic situations, policymakers should establish unified guidelines and health protocols to minimise disruptions caused by the regulatory inconsistencies across different countries. In the long term, policymakers play a crucial role in driving sustainability in aviation industry. To help airlines reduce the GHG emission stemming from flight operations, policymakers could facilitate the adoption of sustainable fuel and the investment in more advanced aircraft by means of subsidies. Finally, promoting the more diversified carbon offset programs and raising passengers' awareness of greener air travel behaviours by policymakers could contribute to lowering emissions and advancing sustainability goals.

In addition to managerial considerations, it is imperative to address the political implications arising from the findings of this study. The aviation industry is inherently intertwined with governmental policies and regulations, and the implications of crises like the COVID-19 pandemic extend to the political realm. Governments play a pivotal role in shaping the operational landscape of airlines, particularly during times of crisis. Therefore, the findings underscore the necessity for policymakers to adopt proactive measures to safeguard the stability and resilience of the aviation sector. Clear political implications emerge, emphasizing the need for coordinated strategies among nations to navigate through crises efficiently. Collaboration on a global scale becomes paramount, with policymakers being urged to establish international frameworks for crisis response and recovery, ensuring consistency and alignment in regulatory measures across borders. Moreover, political leaders must prioritize sustainability in their agendas, recognizing the vital role of aviation in environmental stewardship. This involves not only incentivizing airlines to invest in greener technologies but also enacting robust policies to curb carbon emissions and promote sustainable practices across the industry. By embracing these political implications, governments can foster an environment conducive to the long-term viability and sustainability of the aviation sector in the face of unprecedented challenges.

6. Conclusions

This study extensively evaluated 26 global airlines during the COVID-19 pandemic, spanning the years 2019–2022. Our findings reveal that while overall efficiency is moderately high on average, no airline achieved full efficiency during the pandemic. Efficiency decreased notably from 2019 to 2020, with a partial recovery but not a return to pre-pandemic levels by 2022.

To comprehensively assess dynamic efficiencies across multiple dimensions, we adopted a four-year dynamic system with a network structure, following the theoretical model proposed by Omrani and Soltanzadeh (2016). This model comprises three interconnected sub-stages: operational, service, and financial stages. Notably, we incorporated an undesirable output, namely GHG emissions, within the service stage to account for environmental performance. Comparing the results with those obtained from the dynamic DEA model, our DNDEA model exhibited higher discriminatory power in identifying inefficient units by considering both the internal components and dynamic factors. Specifically, our empirical model computed three types of efficiency scores: overall, period-specific, and stage-specific efficiencies. The research findings indicated that airlines' overall efficiencies were typically below optimal levels. An examination of annual efficiency variations showed a notable decrease in airline efficiencies between 2019 and 2020, followed by partial recovery in the subsequent two years. Nonetheless, as of 2022, the efficiency level still lingered below that of the pre-pandemic period.

Delving deeper into the stage-specific efficiency scores, we observed that the primary source of low efficiency lay within the second and third stages, while the performance of the first stage generally remained satisfactory. Consequently, airline managers should prioritize efforts to improve service and financial efficiency to enhance overall efficiency, especially during crises. This is particularly relevant for budget airlines, which heavily rely on passenger revenue as their primary income source.

Moreover, the suboptimal efficiency identified in the second stage underscores the ongoing need for environmental efficiency enhancements. Given that mitigating the environmental impact of airlines is a gradual process requiring collaboration from various stakeholders, both airlines and policymakers must commit to long-term efforts to achieve optimal environmental efficiency.

While this study provides valuable insights into the performance changes of global airlines during the COVID-19 pandemic, it is crucial to acknowledge its limitations and potential avenues for future research. Firstly, the selected variables, such as operating expenses, ASK, and RPK, were chosen due to data availability constraints. Future research could refine this by including more relevant indicators like environmental abatement costs and on-time arrival/departure rates for a comprehensive analysis.

Secondly, the study's selection of airline samples is primarily based on passenger volume. As a result, the sample is mostly composed of major international airlines, although they are headquartered in different regions such as Western Europe, the United States, and East Asia. Future research aiming to explore regional differences could broaden the range of DMUs and employ a more equitable approach when choosing a diverse set of airline samples.

Thirdly, the greenhouse gas emissions (GHG) has been treated as an input in the model during the service stage analysis; this contradicts principles such as the materials balance principle and the laws of thermodynamics. To rectify this, future research could explore alternative measurements of the CO_2, such as by-production approach or factorially determined multiple equation models. These approaches consider GHG emissions as undesirable outputs and aim to minimise their impact through various strategies such as emission reduction technologies, carbon offsetting, and sustainable fuel usage. Implementing these alternative approaches would ensure an even more accurate representation of the environmental impact of airline operations.

To enhance the model further, alternative network structures could also be considered. The current study employs a sequential model, where outputs of one stage feed into the next. However, Kao (2013) propose two alternative structures: the parallel model, which assesses sub-stages independently, and the mixed model, which combines both sequential and parallel elements. Investigating these alternatives may yield more precise performance assessments and valuable insights for optimizing airline performance.

Finally, it is proposed to explore the application of a parametric approach in future studies. Most existing research in this domain has utilised non-parametric methods like DEA. However, employing a parametric approach could offer complementary insights and allow for result validation. Contrasting the results obtained through parametric methods with those derived from DEA could provide a more robust understanding of airline efficiency and performance dynamics during the COVID-19 pandemic.

CRediT authorship contribution statement

Sijin Wu: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis. **Marios Dominikos Kremantzis:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Umair Tanveer:** Writing – review & editing, Validation, Resources, Methodology, Data curation. **Shamaila Ishaq:** Writing – review & editing, Visualization, Validation, Methodology. **Xianghan O'Dea:** Writing – review & editing, Validation. **Hua Jin:** Writing – review & editing, Methodology.

Appendices.

Appendix A. Dataset

Airline	Year	Passenger Number	GHG	Fleet Size	Number of Employees	Operating Expense	Total Revenue	ASK	RPK	Load Factor
Ryanair	2018			450						
	2019	149	1270	454	17268	8249.72	9512.88	192165	182556	95
	2020	28	290	461	15016	2825.34	1867.58	49271	34982	71
	2021	97	919.33	500	19116	6084.02	5681.66	147028	120563	82
	2022	169	1426.62	537	22261	9823.16	11342.11	229698	213619	93
EasyJet	2018			315						
	2019	96.1	832.45	331	15000	7609.2	8154.53	116056	107741	91.5
	2020	48.1	424.72	342	14000	4928.21	3857.69	62380	58914	87.2
	2021	20.4	211.4	308	13689	2763.41	2005.5	97287	23594	72.5
	2022	69.7	642.14	320	13951	6411.84	7113.44	97287	84874	85.5
Emirates	2018			270						
	2019	46.6	3438	270	60033	23314.44	25060.49	367153	288148	78.5
	2020	6.6	1110.67	259	40801	12519.89	8426.98	64062	28353	44.3
	2021	19.6	1832	262	45843	17193.46	16125.34	159962	93799	58.6
	2022	43.6	2680	260	56379	26348.77	29252.32	225867	225900	79.5
Lufthansa	2018			351						
	2019	72.47	1747.68	364	39381	18053.75	18627.1	212948	175762	82.5
	2020	18	508.81	421	38670	9204.34	4684.93	64480	40064	62.1
	2021	23.54	627.09	389	36545	9169.23	5989.35	82962	50067	60.3
	2022	51.78	1119.45	386	34402	14976.84	13866.32	149412	119363	79.9
British Airways	2018			294						
	2019	47.7	2464.04	305	38788	14519.8	16973.18	186170	155580	83.6
	2020	12.28	941.98	277	34393	8114.1	5129.49	63725	39118	61.4
	2021	10.32	774.91	276	27278	7693.26	5079.78	52635	30700	58.3
	2022	33.03	1477.89	276	29680	13226.88	13600.49	130938	104559	79.9
Turkish Airlines	2018			332						
	2019	74.28	1783.41	350	37670	12644	13229	187717	153203	86.2
	2020	27.95	905.98	363	38648	7264	6734	75009	53253	71
	2021	47.79	1659	370	37561	9411	10405	127781	86708	67.9
	2022	71.8	1817	394	65000	15710	18026	201735	162665	80.6
KLM	2018			214						
	2019	35.09	1203	229	30572	10226.2	12402.02	122452	109476	89.4
	2020	11.23	668	218	29968	5930.37	5844.75	64842	33873	52.2
	2021	14.04	742	218	26607	7177.51	6355.03	82452	40912	49.6
	2022	25.84	907	225	27424	9474.74	11241.05	98660	82289	83.4
Wizz Air	2018			112						
	2019	34.57	331.02	121	4261	2196.19	2596.98	60283.96	55993.95	92.8
	2020	40.03	378.39	131	4440	2765.98	3152.17	69972.52	65680.23	93.6
	2021	10.19	130.34	137	3960	1499.53	874.56	25551.63	16691.57	64
	2022	27.13	264.67	153	4709	2240.74	1750.95	55787.66	43679.18	78.1
Norwegian Air Shuttle	2018			164						
	2019	36.2	606.31	156	9389	2078.61	4945.68	100031	86616	86.6
	2020	6.9	113.54	131	6365	1471	966.02	18168	13680	75.2
	2021	6.2	73.38	51	3310	766.46	589.99	9437	6869	72.8
	2022	17.8	211.15	70	3871	1832.26	1962.66	27382	22757	83.1
American Airlines	2018			1551						

(*continued on next page*)

(*continued*)

Airline	Year	Passenger Number	GHG	Fleet Size	Number of Employees	Operating Expense	Total Revenue	ASK	RPK	Load Factor
	2019	155.82	4114.3	1547	133700	42703	45768	458803.52	388256.49	84.6
	2020	65.76	1983.1	1399	102700	27758	17337	230404.38	147777.65	64.1
	2021	165.68	2881	1432	123400	30941	29882	345259.76	259969.56	75.3
	2022	199.29	3462.9	1461	129700	47364	48971	418792.11	347012.33	82.9
United Airlines	2018			1329						
	2019	162.44	3440.69	1358	95900	38956	43259	458660.29	385211.62	84
	2020	57.76	1548.54	1287	74400	21712	15355	197633.39	118902.87	60.2
	2021	104.08	2137.05	1344	84100	25654	24634	287563.31	207571.06	72.2
	2022	144.3	3040.11	1338	92800	42618	44955	398887.79	332797.03	83.4
Delta Airlines	2018			1316						
	2019	162.26	3732.84	1340	91000	40389	47007	443178.44	382507.93	86
	2020	55.02	1717.49	1090	74000	29564	17095	216197.13	118144.87	55
	2021	102.9	2456.13	1165	83000	28013	29899	312974.79	216765.22	69
	2022	142.62	3074.1	1254	95000	46921	50582	375339.93	314593.78	84
Cathay Pacific Airways	2018			154						
	2019	35.2	1802.5	155	27342	12916.67	12966.56	163244	134397	82.3
	2020	4.6	751.3	199	19452	7141.68	5508.32	34609	20079	58
	2021	0.72	599.7	193	16721	5550.5	5426.99	13228	4120	31.1
	2022	2.8	533.2	181	16462	3491.51	5605.93	20056	14764	73.6
Singapore Airlines	2018			121						
	2019	20.91	1248.2	122	16760	12718.5	13012.7	127165.8	104134.6	81.9
	2020	0.51	273.96	114	16772	5399	3478	19253.7	2669	13.7
	2021	3.39	619.44	123	14526	7180	7068.1	58748.1	19177.7	32.6
	2022	18.16	967.7	133	14803	12988.9	15590.1	106099.3	91025.2	85.8
Scoot	2018			202						
	2019	10.45	202	203	2412	782	212.3	33445.8	28668.5	85.7
	2020	0.08	176	168	1976	782	212.3	2228.2	221.6	9.9
	2021	0.5	55.6	183	1747	886.5	432.9	9822.2	1486.8	15.1
	2022	8.33	152.8	195	2551	1816.9	1965	26932.6	22602.9	83.9
Korean Air	2018			166						
	2019	27.35	1329.18	169	20965	10475.9	10547.55	101108	83273	82.4
	2020	7.5	767.52	159	20072	6357.22	6448.15	34860	19079	54.7
	2021	5.7	754.53	154	19019	6642.64	7882.17	23519	8634	36.7
	2022	10.87	863.12	155	19142	8723.17	10914.96	42374	31621	74.6
Iberia	2018			123						
	2019	22.5	561.31	123	16776	5764.84	4501.68	73354	63991	87.2
	2020	6.8	202.14	113	9817	4189.5	1310.5	25314	17757	70.1
	2021	10.56	297.18	100	11408	3555.03	3294.67	40606	27976	68.9
	2022	19.98	446.34	111	15499	5398.95	5801.05	63904	53826	84.2
Scandinavian Airlines	2018			157						
	2019	29.76	420	158	10445	6754.84	6914.38	52371	39375	75.2
	2020	12.61	180	139	7568	4588.35	3135.59	23365	14127	60.5
	2021	7.59	118.9	129	7532	3094	2220.14	17253	8256	47.9
	2022	17.87	241.4	134	8945	4968.34	4497.46	34371	24317	70.7
China Southern Airlines	2018			840						
	2019	151.63	2852.77	862	103876	21512.45	22339.61	344061.86	284920.82	82.8
	2020	96.86	1946.49	867	100431	15810.9	13412.69	214721.97	153440.11	71.46
	2021	98.5	1924.38	878	98098	18040.01	15761.2	213921.82	152426.29	71.25
	2022	62.64	1449.9	894	97899	17108.8	12922.52	153845.14	102077.7	66.35
China Eastern Airlines	2018			692						
	2019	130.3	2262.29	734	81136	17097.13	17513.9	270254	221779.11	82.06
	2020	74.62	1384.25	734	81157	11341.11	8509.93	152066.39	107273.25	70.54
	2021	79.1	1573.57	758	80321	13447.67	10408.9	160690.39	108803.69	67.71
	2022	42.51	982.36	778	80193	12076.44	6844.44	96210.85	61287.67	63.7
Air China	2018			684						
	2019	115.01	2324.8	699	89824	18181.52	19713.48	287787.61	233176.14	81.02
	2020	68.69	1504.4	707	89373	12321.33	10071.55	156060.66	109830.07	70.38
	2021	69.04	1544.4	746	88395	14803.01	11557.09	152444.53	104625.58	68.63
	2022	38.61	1005.3	762	87190	13613.8	7851.8	96212.39	60354.57	62.73
LATAM Airlines	2018			320						
	2019	74.19	1214.97	342	41719	9689.33	10430.93	149116	124521	83.5
	2020	28.3	561.44	300	28396	5999.96	4334.67	55718	42624	76.5
	2021	40.2	649.76	310	29114	6230.62	5111.35	67636	50317	74.4
	2022	62.47	978	310	32507	8371.73	10569.1	113852	92588	81.3
IndiGo	2018			217						
	2019	75.03	674.64	262	27812	4255.72	5077.53	96240	82540	85.8
	2020	30.69	293.97	285	23711	5067.1	1975.79	45425	31519	69.4
	2021	49.8	431.17	275	26164	4440.93	3508.06	70386	70386	73.6
	2022	85.59	678.95	304	32407	7149.08	6926.68	114359	93889	82
Qantas airway	2018			313						
	2019	55.81	1237.27	314	29745	11451.7	12485.06	151430	127492	84.2
	2020	40.48	934.07	314	28957	11258.09	9812.11	111870	92027	82.3
	2021	15.87	323.68	315	22000	5564.99	4458.3	29374	18557	63.2
	2022	21.26	473.44	322	23500	7396.67	6316.23	50633	34363	67.9
Finnair	2018			81						

(*continued on next page*)

(*continued*)

Airline	Year	Passenger Number	GHG	Fleet Size	Number of Employees	Operating Expense	Total Revenue	ASK	RPK	Load Factor
	2019	14.7	356.71	83	54852	3349.72	3468.87	47188	38534	81.661
	2020	3.49	115.1	83	33835	1681.39	946.58	12937.5	8150	62.995
	2021	2.85	114.69	84	32522	1593.37	992.19	12094	5178	42.815
	2022	9.1	247.8	80	55719	2807.47	2480.63	31298	21157	67.599
Hainan Airline	2018			463						
	2019	81.69	1147.67	361	34048	9701.44	10479.07	174344.58	145366.63	83.38
	2020	37.3	618.78	346	36971	6012.7	4260.4	76877.02	57105.63	74.28
	2021	41.3	689.26	344	36892	6635	5272.45	83838.99	62615.63	74.69
	2022	21.07	455.79	342	34576	5139.18	3393.82	49520.49	33515.08	67.68

Appendix B. Formulae of Dynamic DEA model

The following formulae of dynamic DEA model are drawn from the study by Kao (2013):

$$E_j^{sys} = \max\left(\sum_{r=1}^{R} u_r Y_{rj} + \sum_{l=1}^{L} f_l C_{lj}^{(T)}\right) \tag{B.1}$$

Subject to:

$$\sum_{i=1}^{K} v_i X_{ij} + \sum_{l=1}^{L} f_l C_{lj}^{(t_0)} = 1 \tag{B.12}$$

$$\sum_{r=1}^{R} u_r Y_{rj} + \sum_{l=1}^{L} f_l C_{lj}^{(T)} - \left(\sum_{i=1}^{K_s} v_i X_{ij} + \sum_{l=1}^{L} f_l C_{lj}^{(t_0)}\right) \leq 0 \tag{B.13}$$

$$\sum_{r\in r^1} u_r Y_{rj}^{(t,1)} + \sum_{l\in l^1} f_l C_{lj}^{(t)} - \left(\sum_{i\in i^1} v_i X_{ij}^{(t,1)} + \sum_{l\in l^1} f_l C_{lj}^{(t-1)}\right) \leq 0 \tag{B.4}$$

$$v_i, u_r, f_l \geq \varepsilon, i = 1, \ldots, K;\ r = 1, \ldots, R;\ \ l = 1, \ldots L \tag{B.5}$$

$$E_j^{sys} = \frac{\sum_{r=1}^{R} u_r^* Y_{rj} + \sum_{l=1}^{L} f_l^* C_{lj}^{(T)}}{\sum_{i=1}^{K} v_i^* X_{ij} + \sum_{l=1}^{L} f_l^* C_{lj}^{(t_0)}} \tag{B.6}$$

$$E_j^{(t,sys)} = \frac{\sum_{r=1}^{R} u_r^* Y_{rj}^{(t)} + \sum_{l=1}^{L} f_l^* C_{lj}^{(t)}}{\sum_{i=1}^{K} v_i^* X_{ij}^{(t)} + \sum_{l=1}^{L} f_l^* C_{lj}^{(t-1)}} \tag{B.7}$$

where $X_{ij}^{(t)}$, $Y_{rj}^{(t)}$, and $C_{lj}^{(t)}$ denote the *i*th input, *r*th output, and *l*th carry-over of *j*th DMU in period *t*. And the corresponding multipliers are denoted by v_i, u_r, and f_l, respectively. In addition, $C_{lj}^{(t_0)}$ is the initial carry-over entering the system in the first period, while $C_{lj}^{(T)}$ is the carry-over flowing out in the last period *T*.

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