



Article citation information:

Asker, V. Measuring operational and revenue productivity at airports before and after the Covid-19 pandemic: application at selected airports in Turkey. *Scientific Journal of Silesian University of Technology. Series Transport*. 2026, **132**, 33-56. ISSN: 0209-3324. DOI: <https://doi.org/10.20858/sjsutst.2026.132.2>

Veysi ASKER¹

MEASURING OPERATIONAL AND REVENUE PRODUCTIVITY AT AIRPORTS BEFORE AND AFTER THE COVID-19 PANDEMIC: APPLICATION AT SELECTED AIRPORTS IN TURKEY

Summary. The aim of this study is to measure the operational and revenue productivity of 43 airports operated by the State Airports Authority (DHMI) in Türkiye before and after the Covid-19 pandemic. Within the scope of the study, in order to obtain more reliable results from the productivity analysis, airports were divided into two groups (First and Second Groups) based on passenger numbers for the 2019-2024 period and analysed. Firstly, the input and output variables for airports were weighted using the ENTROPY method. The analysis conducted using the ENTROPY method revealed that the variables 'Terminal Size', 'Non-aeronautical Revenues' and 'Aeronautical Revenues' are critical importance to airport productivity. Then, the operational and revenue productivity of the airports was measured using the EATWIOS method. The research results showed that, among the airports in the first group, Antalya (AYT) Airport had the highest productivity in terms of both operational and revenue productivity. Among the airports in the second group, Hatay (HTY), Batman (BAL), and Denizli (DNZ) airports were found to have the highest operational and revenue productivity in different periods.

Keywords: Airport Productivity, Covid-19, ENTROPY Method, EATWIOS Method

¹ Faculty School of Civil Aviation, Dicle University Fetih Campus, 21280 Diyarbakır, Türkiye. Email: veysi.asker@dicle.edu.tr. ORCID: <https://orcid.org/0000-0002-8969-7822>

1. INTRODUCTION

The air transport sector continues to be a widely used mode of transport, with airports playing a significant role in supporting the sector's development as key infrastructure points [41]. Increasing globalization and liberalization have contributed to the expansion of air traffic on a global scale, and airports have been seen to significantly support international trade, tourism, and economic growth [31]. With the anticipated growth in the air transport sector, an efficient and productive airport system has become crucial for maintaining global competitiveness [27]. In this regard, it is crucial to examine the performance of airports, develop effective operational strategies and increase productivity [7]. The productivity of airports largely depends on the effective use of fixed assets and the ability to produce maximum output by effectively utilizing existing inputs [31].

Increasing productivity at airports will save time and reduce costs for both users and airport management. Increasing productivity will contribute to reducing congestion and delays, thereby enhancing the quality of service experienced by passengers [22]. Furthermore, establishing specific standards to accurately assess and compare the performance of airports would be highly beneficial for airport management and stakeholders. The design and implementation of inspection, monitoring and evaluation procedures applicable to all airports will help airports with low productivity to identify their shortcomings and improve their productivity. It is also crucial to identify the factors that determine the productivity of airports [10]. Today, airport productivity assessments are of great importance to airlines, regulatory bodies, airport management, shareholders, and passengers [7]. The reasons for researching productivity at airports include evaluating various investment approaches, auditing airport operations, and assessing operational and financial productivity [26]. In recent years, it is known that the relevant authorities have also conducted productivity assessments at airports in order to evaluate the productivity of airport ownership models and to investigate the potential benefits that would arise from private sector participation [44]. The literature on evaluating the productivity of airports has grown rapidly in recent years [8].

The Covid-19 pandemic that emerged in China in the final months of 2019 spread globally in 2020, causing significant disruptions to global air transport operations [37]. Historically, there have been numerous crises and pandemics, including the Gulf War (1991), the Asian financial crisis (1998), the 9/11 attacks (2001), the SARS pandemic (2003), the global financial crisis (2008-2009), and the MERS pandemic (2012). However, none of them caused such a dramatic decline in global aviation revenues and volumes as the Covid-19 pandemic [17]. The border closures, quarantine measures and travel restrictions implemented worldwide in response to the spread of the Covid-19 pandemic have seriously affected the air transport sector and airports, which are one of the sector's key stakeholders. In particular, border closures and flight ban in 2020 led to the cessation of international travel and caused airports to operate below capacity [36]. The strict border controls and limited vaccine availability implemented in 2021 caused the pandemic's devastating effects to last longer. During this period, many airports experienced serious disruptions in their performance [6]. Although restrictions began to be eased in North America and Europe from the beginning of 2022, restrictions in the Asia-Pacific region began to be eased in mid-2022. The Airports Council International (ACI) predicted that airports would return to pre-pandemic passenger levels by the end of 2023 or the beginning of 2024 [1].

The destructive effects of the Covid-19 pandemic have been seen at airports in Turkey, as in other countries. Passenger traffic, which stood at around 209 million before the pandemic (2019), fell by 61 percent to 81 million in 2020 [11]. In the following years, as the impact of

the pandemic diminished, there was an increase in passenger and aircraft traffic. There are studies in the literature analysing the productivity of airports in Turkey during the pandemic period [13, 18, 21]. These studies compare the productivity of airports before and during the pandemic. However, there are very few studies in the literature comparing the pre- and post-pandemic productivity of airports in Turkey [2]. Furthermore, these studies have only compared the operational productivity of airports. In this study, the operational and revenue productivity of airports in Turkey during the pre- and post-pandemic periods have been analysed. From this perspective, it is believed that this study will fill this gap in the literature.

Airport performance is fundamentally based on operational and revenue productivity. Operational productivity measures whether inputs are being used efficiently to produce the existing output level with the current inputs. From this perspective, operational productivity consists of inputs such as terminal size, runways and employees. Revenue productivity measures whether maximum revenue is being generated from the volume of production at airports. In this context, revenue productivity includes inputs such as passenger and cargo traffic [20]. For Turkey, which allocates a significant portion of its total public budget to transport infrastructure, it is crucial to analyse and evaluate the operational and revenue productivity of airports in Turkey. However, no studies have been found in the literature examining the operational and revenue productivity of airports in Turkey using the integrated Entropy-EATWIOS method. In this regard, it is believed that this study will contribute to the existing literature.

The reasons for using the ENTROPY method in this study can be explained as follows: (a) the calculations are few in number and simple, (b) the normalization process is performed regardless of the benefit and cost characteristics of the criteria, (c) there is no limitation on the number of criteria used, (d) no additional calculations are required due to the large number of criteria [39]. The reason for using the EATWIOS method is: (a) having fewer application steps compared to other productivity analysis methods, (b) being easy to use without requiring advanced mathematical knowledge, (c) not requiring any software program during use, (d) its ability to demonstrate whether the outputs obtained are satisfactory for decision-makers, (e) its ability to allow for the separate evaluation of the effects of both input and output variables on performance [47].

In this study, a two-stage analysis was adopted with the aim of filling the research gap. In the first stage, the input and output variables were weighted using the Entropy method. In the second stage, the productivity of airports was analysed using the EATWIOS method. The study analysed the operational and revenue productivity of airports operated by the State Airports Authority (DHMI) in Turkey before and after the pandemic.

The remainder of the study is organized as follows. Chapter 2 summarizes the literature review. Chapter 3 provides information on the methodology. Chapter 4 presents the empirical findings. Chapter 5 includes conclusions, limitations, and future research.

2. LITERATURE

A general literature review has shown that the analysis of airport productivity has attracted considerable interest and that numerous studies have examined airport performance from different perspectives. The studies listed in Table 1 summarize the relevant literature. These studies show that Data Envelopment Analysis (DEA) is the most commonly used method in airport productivity analysis. In some studies, unlike classical DEA, a two-stage approach [3], super-efficiency [23], weight restricted [18], bootstrap [5], and network [41]. (DEA models

were used. Some researchers, however, in addition to the DEA with Classification and Regression Trees (CART) [31], Fixed Proportion Ratio (FPR) [21], Truncated Regression Analysis [10], Principal Component Analysis (PCA) [12] and Panel Regression Analysis [36] have used such methods. There are a few studies in the literature where DEA and Multi-Criteria Decision Making (MCDM) methods are used together [24, 43].

Tab. 1

Key studies on the productivity of airports

Authors	Country	Methods	Periods	Input	Output
(Song et al. 2025) [36]	China	NDEA and Panel regression analysis	2015-2019	Aircraft stands, Subsidy amount, Runway length, Terminal area	Aircraft movements, Real GDP, Urban Employment, Tertiary industry, Cargo movement
(Domingos et al. 2025) [12]	Brazil	DEA and Principal Component Analysis (PCA)	2015-2023	Total length of the landing and take-off runway, Passenger terminal area	Cargo movement, Aircraft movements, Passenger movement
(Güner et al. 2024) [18]	Turkey	Weight-restricted NDEA	2017-2021	Terminal area, Runway area, Apron area, Special Purpose Vehicle Inventory, Tourist Arrivals, Population, Socio-Economic Development Degree Centrality, Eigenvector Centrality, Betweenness Centrality	Workload Unit, Aircraft Movements

(Güner and Seçkin Codal 2024) [21]	Turkey	Fixed Proportion Ratio and Malmquist Index	2017-2020	Terminal area, Runway area	Workload Unit, Aircraft Movements
(Wang et al. 2023) [41]	China	Two Stage NDEA	2016-2019	Terminal area, Total cost of revenue Runway area	Airport non-aeronautical revenue
(Cifuentes-Faura and Faura-Martínez 2023) [10]	Spain	Bootstrap DEA and Truncated regression	2018	Runway area, Boarding Gates	Passengers, Aircraft Movements
(Kaya et al. 2022) [23]	Turkey	Super-Efficiency DEA	2018	Terminal area, Runway length, Total expenditures, Employees, Gates, Check-in counters, Bridges, Park positions, Runways, Apron area	Total Freight, Total Cargo, Passenger Carried, Service Sales Revenues, Flight Traffic
(Yilmaz et al. 2022) [43]	Turkey	Fuzzy AHP /DEA	2015-2018	Terminal area, Runway length, Total expenditures, Employees, gates, Check-in counters	Total revenue, Passengers, Amount of cargo carried, Aircraft Movements
(Özsoy and Örkücü 2021) [31]	Turkey	Bootstrap DEA and CART (Classification and Regression Trees)	2013	Terminal area, Runways, Capacity of the car park, All vehicles, Total expenditures, Employees,	Total revenue, Passengers, Amount of cargo carried,

(Keskin and Köksal 2019) [24]	Turkey	AHP/DE A-AR	2015	Employees, Gates, Runway area, Operating expenditures, Terminal area	Total revenue, Passengers, Aircraft Movements, Amount of cargo carried
(Augustyniak et al. 2015) [3]	Germany and Poland	Two-Stage DEA	2000-2010	Terminal area, Personnel costs, Employees, Capital cost	Amount of Cargo Carried, Aircraft Movements, Passengers, Total revenue
(Chang et al. 2013) [5]	China	Bootstrap DEA	2008	Terminal size, Runway length, Operating Hour	Aircraft Movements, Amount of Cargo Carried, Passengers

Tables 1 illustrate the methods used in the efficiency analysis and performance measurement of airports, while also providing important information on how the output and input variables used in this study are determined. When examining the studies presented in the table, it can be seen that the output variables consist of sales, revenue, aircraft traffic, cargo traffic and passenger traffic, while the input variables are more varied. In particular, it can be seen that input variables such as runway number, number of staff, costs and terminal size are preferred other input variables.

Despite the extensive literature on airport productivity analysis, it has been observed that MCDM methods such as EATWIOS are rarely used in the productivity analysis of airports in Turkey [38]. It examined the operational productivity of selected airports in Turkey for the period 2014-2018 using the Weight Restricted EATWOS and Equally weighted EATWOS methods. Subsequently, the productivity values obtained were compared with the input-oriented DEA model. The analysis revealed that the productivity values obtained using the Weight Restricted EATWOS and Equally Weighted EATWOS methods produced more realistic results compared to the input-oriented DEA model. [25] They examined the performance of the ten largest airports in Turkey in terms of passenger numbers for the period 2013-2019 using the CRITIC-EDAS method. The analysis showed that there were no significant changes in the performance ranking of the airports. This article examines the operational and revenue productivity of airports separately using more variables.

There are some critical gaps in the literature regarding the productivity analysis of airports in Turkey. The first of these gaps relates to revenue performance. The total revenue variable has been used as an output variable in the majority of productivity models [24, 26, 31, 43]. However, very few studies have distinguished between non-aviation and aviation revenue [20]. However, it has been observed in the international literature that aviation and non-aviation revenue are examined separately due to their differing effects on airport performance [9, 14, 41]. This study has a productivity analysis by distinguishing between aviation and non-aviation

revenues at airports in Turkey. The second critical gap in the literature on the productivity analysis of airports in Turkey is that, there are very few studies examining the productivity analysis of airports during the Covid-19 pandemic. [21], They evaluated the productivity analysis of airports in Turkey for the 2017-2020 period using the Fixed Proportion Ratio and Malmquist Index methods. The analysis revealed that airports serving domestic routes were more efficient than those serving international routes. [18], They evaluated the productivity analysis of airports in Turkey for the 2017-2021 period using the CRITIC-NDEA method. As a result of the analysis, they found that the productivity values of medium-sized airports were very low. This article examines the operational and revenue productivity of airports in Turkey during the pre-pandemic period (2019), the pandemic period (2020-2021), and the post-pandemic period (2022-2024). A review of the literature revealed no studies examining the operational and revenue productivity of airports in Turkey during the pre-pandemic and post-pandemic periods. Therefore, this study is expected to make significant contributions to the literature.

3. DATA AND METHODOLOGY

The main objective of this study is to examine the operational and revenue productivity of airports operated by the State Airports Authority (DHMI) in Turkey before and after the Covid-19 pandemic. Therefore, a six-year period spanning from 2019 to 2024 has been selected. An integrated method combining Entropy and EATWIOS methods has been proposed to examine the productivity of airports. In this context, firstly Airports operated by the State Airports Authority (DHMI) in Turkey have been determined. The International Air Transport Association (IATA) codes for the airports are shown in Table 2.

Tab. 2

IATA codes for airports in Turkey

IATA Codes	Airports	IATA Codes	Airports
ADA	Adana	SAW	İstanbul Sabiha Gökçen
ESB	Ankara Esenboğa	ADB	İzmir Adnan Menderes
ADF	Adıyaman	KCM	Kahramanmaraş
AJI	Ağrı Ahmed-i Hani	NAV	Kapadokya
MZF	Amasya Merzifon	KSY	Kars Harakani
AYT	Antalya	KFS	Kastamonu
CII	Aydın Çıldır	ASR	Kayseri
EDO	Balıkesir Koca Seyit	KCO	Kocaeli Cengiz Topel
BZI	Balıkesir Merkez	KYA	Konya
BAL	Batman	MLX	Malatya
BGG	Bingöl	MQM	Mardin
YEI	Bursa Yenişehir	DLM	Muğla Dalaman
CKZ	Çanakkale	BJV	Muğla Milas-Bodrum
COV	Çukurova	MSR	Muş Sultan Alparslan
DNZ	Denizli Çardak	OGU	Ordu Giresun
DIY	Diyarbakır	RZV	Rize- Artvin
EZS	Elâzığ	SZF	Samsun-Çarşamba

AOE	Eskişehir Hasan Polatkan	SXZ	Siirt
ERC	Erzincan Yıldırım Akbulut	NOP	Sinop
ERZ	Erzurum	VAS	Sivas Nuri Demirağ
GZT	Gaziantep	GNV	Şanlıurfa GAP
GZP	Gazipaşa Alanya	NKT	Şırnak Şerafettin Elçi
GKD	Gökçeada	TEQ	Tekirdağ Çorlu
YKO	Hakkâri Yüksekova	TJK	Tokat
HTY	Hatay	TZX	Trabzon
IGD	Iğdır Şehit Bülent Aydın	USQ	Uşak
ISE	Isparta Süleyman Demirel	VAN	Van Ferit Melen
IST	İstanbul Atatürk	KZR	Zafer
ISL	İstanbul İGA	ONQ	Zonguldak Çaycuma

After listing the airports in Turkey, the input and output variables to be used to perform the productivity analysis of the airports were determined. Performance dimensions were taken into account when determining the input and output variables.

Airport production systems encompass multiple performance dimensions [28]. Combining numerous production systems under a single model complicates the management of trade-offs between performance dimensions of different structures [34]. Furthermore, combined models weaken the discriminatory power of performance measurement methods [19]. In this regard, many studies in the literature have addressed airport performance separately in different dimensions [20, 31, 42]. In this regard, airport productivity analyses were measured in this study from two perspectives.

The first dimension is an operational productivity model that aims to measure whether inputs are being used efficiently to produce the current output level with the available inputs. In this regard, an operational productivity model consisting of three inputs (employees, runways, terminal size) and two outputs (cargo traffic and passengers) has been created. The second dimension is the revenue productivity model, which aims to measure whether maximum revenue is being generated from the volume of production at airports. The input variables for this model are passengers, cargo traffic and cost while the output variables are aviation and non-aviation revenues [20]. Aviation revenue consists of terminal services such as aircraft parking services, space allocation services and ground services, as well as air traffic control services such as transit passage, landing, navigation, approach and airport information systems [29]. Non-aviation revenue consists of rental income from facilities located at airports, passenger services, international passenger security services, communications and announcements, and other operating service revenues [30]. Non-aviation revenues provide airport management with opportunities to generate additional income and constitute a significant portion of total revenue. Furthermore, non-aviation revenues subsidize aviation-related operations [9]. Due to the increasing importance of non-aviation revenues at airports today, the ability of the airports included in this study to generate non-aviation revenues has been measured separately.

The data for the period 2019-2024 was examined, taking into account the input and output variables selected for the study. Some airports (AOE, COV, GZP, ISL, SAW, KZR, ONQ) were excluded from the analysis as financial and labour force data could not be obtained because they are operated by the private sector. Some airports (BZI, CII, GKD, KCO) were excluded

from the analysis due to low traffic volumes, while others (IST, RZV, TJK, USQ) were excluded due to data gaps.

The airport system in Turkey exhibits a heterogeneous structure, with a significant portion of air traffic concentrated in a few major airports. This heterogeneous structure is even more pronounced in international flights. Due to this heterogeneous structure, studies analyzing productivity at airports in Turkey have been scaled based on criteria such as passenger numbers and flight numbers, and airports have been classified according to these scales [23, 31, 38]. This enables the creation of more comparable airport groups. The same approach has been adopted in this study. To create a more homogeneous sample, airports with an annual passenger count exceeding 700,000 were included in Group 1, while those with an annual passenger count below 700,000 were included in Group 2. This classification is based on the year 2024, when the effects of the Covid-19 pandemic have completely subsided and the number of flights has returned to pre-pandemic levels. Group 1 and Group 2 airports are shown in Table 3 according to their IATA codes.

Tab. 3

First and second group airports

The First Group Airports	The Second Group Airports
ADA	ADF
ESB	AJI
AYT	MZF
DIY	EDO
EZS	BAL
ERZ	BGG
GZT	YEI
ADB	CKZ
NAV	DNZ
ASR	ERC
KYA	YKO
MLX	HTY
MQM	IGD
DLM	ISE
BJV	KCM
OGU	KSY
SZF	KFS
GNY	MSR
TZX	SXZ
VAN	NOP
	VAS
	NKT
	TEQ

The data used in the study covers a six-year period from 2019 to 2024. This timeframe has enabled us to observe both how the productivity analysis of airports has changed over the years and the impact of the Covid-19 pandemic on airport productivity. All data used in the research are secondary data obtained from DHMI's annual activity reports. After the input-output

variables were determined and the decision-making units (DMUs) were classified, the productivity analysis of airports was performed using the Entropy-EATWIOS integrated method.

3.1. ENTROPY Method

In multi-criteria decision-making problems, there is no equality among all selection criteria; each selection criterion has a relative importance. From this perspective, in order to perform a successful performance analysis, it is necessary to calculate the relative weight values of the selection criteria. The weight of the selection criteria expresses the relative importance of each variable involved in the decision-making process [16]. There are many subjective and objective methods developed to calculate the weighting of selection criteria [46]. In subjective methods, weighting is performed based on the assessments of decision-makers, whereas in objective methods, more objective and secondary data are used, and the opinions of decision-makers are not required [39]. Among objective methods, one of the most commonly used methods is the Entropy Method. The concept of entropy was developed by Shannon in 1948 in mathematical communication theory to measure uncertainty [33].

As the data used in this study is entirely objective and secondary data, the Entropy Method was utilized in the weighting process of the selected criteria. Since the Entropy Method will be integrated into the EATWIOS method, the weighting process of the input and output values was performed separately. The application steps of the Entropy Method are shown below [16, 46].

Step 1: In the first step of the Entropy Method, a decision matrix is created for both the input variables (A) and the output variables (B), as shown in Equation (1-2).

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1j} \\ a_{21} & a_{22} & \dots & a_{2j} \\ \dots & \dots & \dots & \dots \\ a_{i1} & a_{i2} & \dots & a_{ij} \end{bmatrix} \quad (1)$$

$$B = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1k} \\ b_{21} & b_{22} & \dots & b_{2k} \\ \dots & \dots & \dots & \dots \\ b_{i1} & b_{i2} & \dots & b_{ik} \end{bmatrix} \quad (2)$$

Step 2: In the second step of the method, the input and output criteria are normalized using Equation (3-4), without distinguishing between the cost and benefit functions.

$$A_{ij} = \frac{a_{ij}}{\sum_{i=1}^j a_{ij}} \quad (3)$$

$$B_{ik} = \frac{b_{ik}}{\sum_{i=1}^j b_{ik}} \quad (4)$$

Step 3: In the third step of the method, the entropy value of the input variables (C_j) and the entropy value of the output variables (D_k) are calculated using Equation (5-6).

$$C_j = \left\{ \frac{-1}{\ln x} \right\} \sum_{i=1}^x [A_{ij} * \ln(A_{ij})]; \forall j \quad (5)$$

$$D_k = \left\{ \frac{-1}{\ln x} \right\} \sum_{i=1}^x [B_{ik} * \ln(B_{ik})]; \forall j \quad (6)$$

The value (x) in the formula represents the number of alternatives.

Step 4: In the fourth step of the method, the differentiation degree of the input variables (P_j) and the differentiation degree of the output variables (U_k) are calculated using Equation (7-8).

$$P_j = 1 - C_j; \forall j \quad (7)$$

$$U_k = 1 - D_k; \forall k \quad (8)$$

Step 5: In the final step of the method, the weights of the input variables and the weights of the output variables are calculated using equation (9-10).

$$W_j = \frac{P_j}{\sum_{j=1}^y P_j}; \forall j \quad (9)$$

$$V_k = \frac{U_k}{\sum_{k=1}^n U_k}; \forall k \quad (10)$$

3.2. EATWIOS Method

EATWIOS (Efficiency Analysis Technique with Input and Output Satisficing) The EATWIOS method was developed by Peters and Zelewski. Initially referred to as EATWOS, the method was developed by [32] to include the assessment of satisfaction levels of input factors and was subsequently renamed EATWIOS. Satisfaction levels were integrated into the EATWIOS method based on Simon's [35] satisfaction theory [4]. The application steps of the EATWIOS method are detailed below [15, 38, 45].

Step 1: In the first stage of the method, decision matrices consisting of input (A) and output (B) variables are arranged separately as shown in equation (1-2).

Step 2: In the second stage of the method, the decision matrixes for the input and output variables are normalized using equation (11-12).

$$A_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^j a_{ij}^2}} \quad (11)$$

$$B_{ik} = \frac{b_{ik}}{\sqrt{\sum_{i=1}^j b_{ik}^2}} \quad (12)$$

After the normalization process is completed, the 'S' matrix for the input variables and the 'R' matrix for the output variables are created, as shown in equation (13-14).

$$S = \begin{bmatrix} s_{11} & s_{12} & \dots & s_{1j} \\ s_{21} & s_{22} & \dots & s_{2j} \\ \dots & \dots & \dots & \dots \\ s_{i1} & s_{i2} & \dots & s_{ij} \end{bmatrix} \quad (13)$$

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1k} \\ r_{21} & r_{22} & \dots & r_{2k} \\ \dots & \dots & \dots & \dots \\ r_{i1} & r_{i2} & \dots & r_{ik} \end{bmatrix} \quad (14)$$

Step 3: At this stage, distance measures indicating how close or how far each variable is from the ideal are determined. However, there are two different applications for input and output variables in this process. For input variables, the smallest value in each column of the input matrix is first identified, as shown in Equation (15). Distance dimensions for the input variables are then calculated using Equation (16).

$$s_j^- = \min\{s_j\}; \forall j = 1, 2, \dots, j \quad (15)$$

$$ip_j = 1 + (s_{ij} - s_j^-); \forall i = 1, 2, \dots, k \quad (16)$$

For the output variables, the maximum value of each column of the output matrix is determined as shown in Equation (17). Subsequently, the distance dimensions for the output variables are calculated using Equation (18).

$$r_k^- = \max\{r_k\}; \forall k = 1, 2, \dots, k \quad (17)$$

$$op_k = 1 - (r_k^- - r_{ik}); \forall i = 1, 2, \dots, j \quad (18)$$

Step 4: At this stage of the method, the weight values obtained for the input and output variables as a result of the entropy method are multiplied separately by the distance dimension values of the input and output variables obtained in the previous stage, as shown in equation (19-20), thereby weighting the distance dimensions.

$$ip_{ja} = ip_j * W_j \quad (19)$$

$$op_{ka} = op_k * V_k \quad (20)$$

Step 5: In the next stage of the method, the weighted distance dimensions of the input and output variables are summed using Equation (21-22).

$$E_i = \sum_{j=1}^x ip_{ja}; \forall i \in j \quad (21)$$

$$L_i = \sum_{k=1}^x op_{ka}; \forall i \in k \quad (22)$$

Step 6: In the final stage of the method, the productivity value (P_i) for each decision-making unit is calculated using Equation (23).

$$P_i = \frac{L_i}{E_i}; \forall i \in I \quad (23)$$

Decision-making units (DMUs) are ranked according to their (P_i) values. The alternative with the highest (P_i) value is considered the most efficient alternative.

4. RESULTS

In this section, the operational and revenue productivity of 43 airports operated by DHMI in Turkey before and after the Covid-19 pandemic has been analysed using the Entropy-EATWIOS integrated model. The airports were divided into two groups (first and second groups) based on passenger numbers for the 2019-2024 period to ensure more reliable results from the productivity analysis.

4.1. ENTROPY Results

In this section, firstly, initial decision matrices containing the input and output variables (criteria) for the first and second groups of airports (alternatives) were created. Then, the weights of the criteria in these decision matrixes were determined using the Entropy method. As this study examined both the operational and revenue productivity of airports, the weighting of the variables used in the analysis was performed separately.

Figure 1 and Figure 2 show the weight changes of the variables used in operational productivity measurement both over time and within themselves. Accordingly, it has been determined that terminal size (Input) is the variable with the highest level of importance for both the first and second groups of airports throughout the entire period. This finding indicates that terminal size has a high level of importance on the operational productivity of both first group and second group airports. It is observed that Cargo Traffic (Output) has a higher level of importance at first group airports compared to second group airports, while Passengers (Output) has a higher level of importance at second group airports compared to first group airports. It is thought that this situation may be due to the greater volume of cargo transported at first-group airports. It has been determined that the importance level of Labor (Input) is higher at first group airports than at second group airports. This situation is thought to stem from the higher number of employees working at first group airports. The importance level of Number of Runways (Input) was found to be the lowest variable for both groups.

Figure 3 and Figure 4 show the weight changes of the variables used in revenue productivity measurement both over time and within themselves. Non-Aeronautical Revenues (Output) was found to be the variable with the highest level of importance throughout the entire period for first-group airports and for the 2019-2022 period for second-group airports. This finding indicates that Non-Aeronautical Revenues have a high level of importance of the productivity of first-group airports. This situation applies only to second-group airports for the 2019-2022 period. Aeronautical Revenues (Output) was found to be the variable with the highest level of importance for second- group airports in the 2023-2024 period. This finding indicates that the level of importance of aeronautical revenues on the productivity of second-group airports increased in the 2023-2024 period. Additionally, it has been determined that the importance

level of the Aeronautical Revenues (Output) and Passengers (Input) variables is higher in the second group of airports compared to the first group. This situation is thought to stem from the lower levels of non-aeronautical revenues and cargo volumes transported at the second group of airports. It was found that the importance level of Cost (Input) is higher for first-group airports compared to second-group airports. However, it was observed that Cost (Input) is the variable with the lowest importance level for both groups.

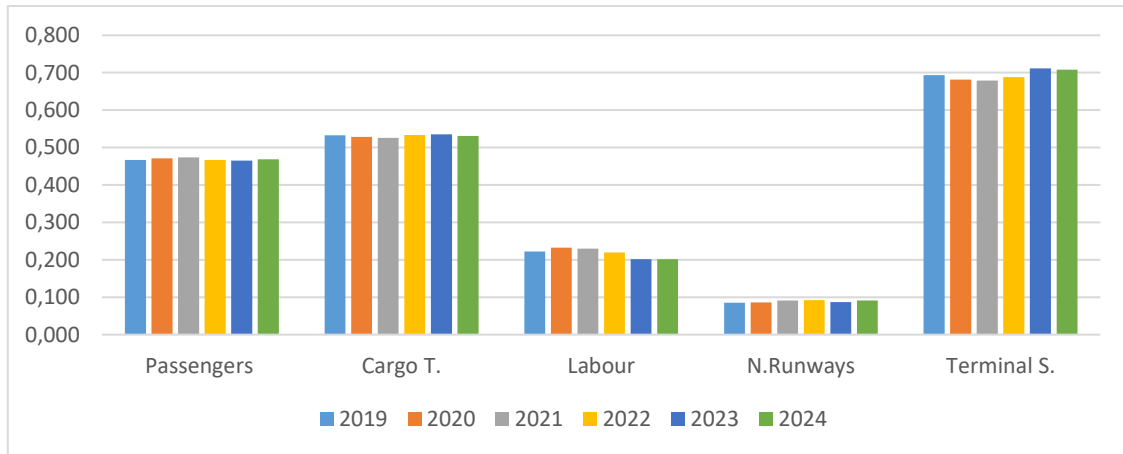


Fig. 1. Criterion weights for first group airports according to the entropy method (Operational Productivity)

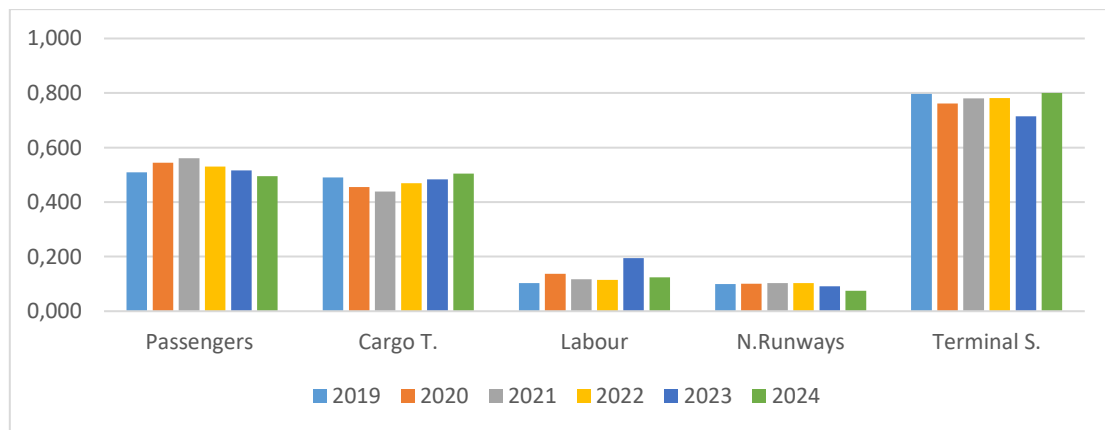


Fig. 2. Criterion weights for second group airports according to the entropy method (Operational Productivity)

4.2. EATWIOS Results

In this section, the operational and revenue productivity of first and second group airports has been evaluated using the EATWIOS method. Firstly, the operational and revenue productivity of first group airports was examined. The operational and revenue productivity scores and rankings of first group of airports are shown in Table 4 and Table 5 respectively.

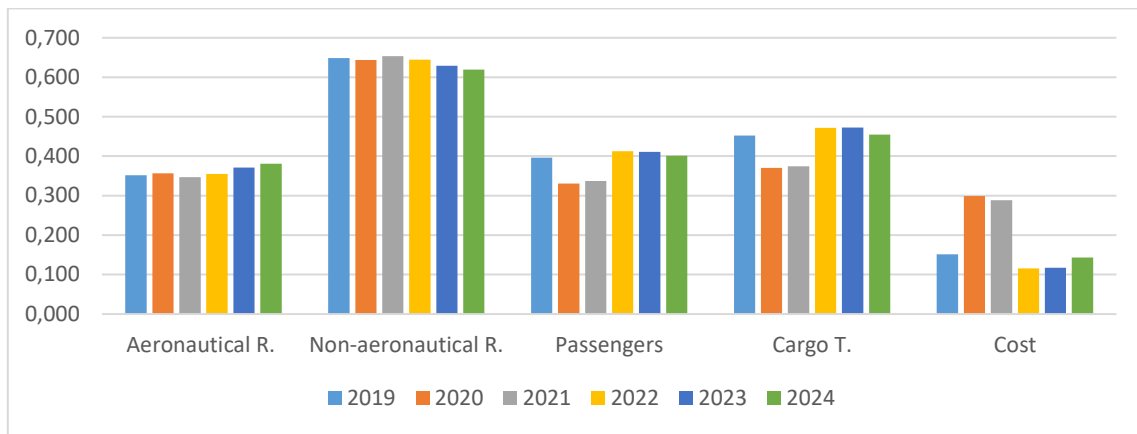


Fig. 3. Criterion weights for first group airports according to the entropy method (Revenue Productivity)

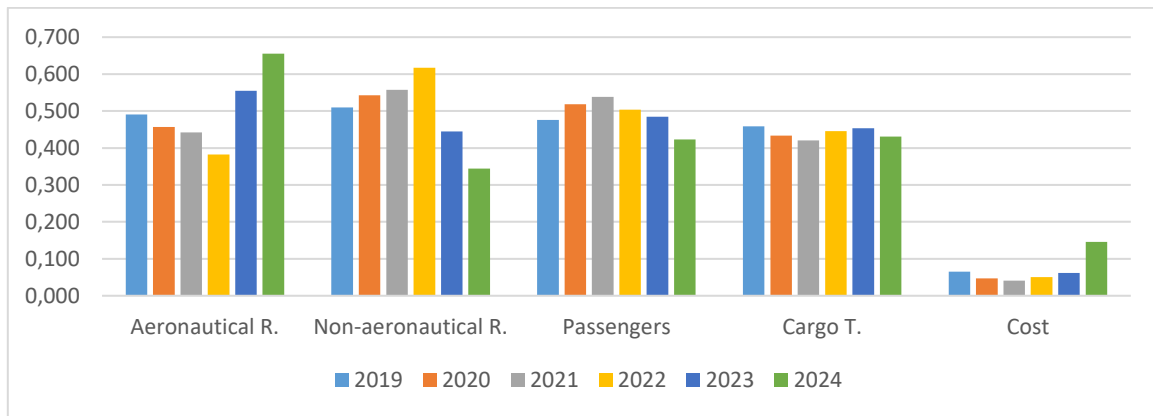


Fig. 4. Criterion weights for second group airports according to the entropy method (Revenue Productivity)

Tab. 4

First group EATWIOS results (Operational productivity)

A	2019		2020		2021		2022		2023		2024	
	S	R	S	R	S	R	S	R	S	R	S	R
ADA	0,471	5	0,243	6	0,289	6	0,222	6	0,228	6	0,183	8
ESB	0,994	3	0,646	3	0,631	3	0,515	3	0,577	3	0,58	3
AYT	0,998	1	0,996	1	0,995	1	0,997	1	0,994	1	0,998	1
DIY	0,386	8	0,179	10	0,207	10	0,167	10	0,174	9	0,176	10
EZS	0,309	15	0,143	16	0,161	18	0,127	16	0,133	15	0,134	15
ERZ	0,313	14	0,146	14	0,169	14	0,131	14	0,135	14	0,137	14
GZT	0,381	9	0,184	8	0,234	8	0,189	8	0,191	8	0,196	7
ADB	0,996	2	0,868	2	0,973	2	0,834	2	0,803	2	0,822	2
NAV	0,273	20	0,132	20	0,146	20	0,118	20	0,123	20	0,126	20
ASR	0,365	10	0,182	9	0,211	9	0,175	9	0,171	10	0,182	9
KYA	0,315	13	0,15	13	0,171	13	0,134	13	0,137	13	0,138	13

MLX	0,304	17	0,139	17	0,162	17	0,125	18	0,128	18	0,129	19
MQM	0,302	18	0,138	18	0,164	16	0,126	17	0,13	17	0,131	17
DLM	0,62	4	0,388	4	0,352	4	0,372	4	0,378	4	0,393	4
BJV	0,457	6	0,272	5	0,301	5	0,259	5	0,249	5	0,247	5
OGU	0,308	16	0,145	15	0,165	15	0,128	15	0,133	15	0,132	16
SZF	0,333	12	0,157	11	0,183	12	0,14	12	0,144	12	0,145	12
GNV	0,293	19	0,137	19	0,156	19	0,122	19	0,127	19	0,13	18
TZX	0,408	7	0,214	7	0,245	7	0,201	7	0,201	7	0,202	6
VAN	0,339	11	0,154	12	0,184	11	0,141	11	0,146	11	0,147	11

Note: A: Airport; S: Score; R: Rank

Based on Table 4, Antalya Airport (AYT) was found to be the most operationally productive airport within the first group of airports throughout the entire period. Considering that Antalya is a major tourist city, this result is not surprising. It has been determined that Kapadokya (NAV) airport has the lowest operational productivity throughout the entire period. Among the plausible reasons for this situation is that tourists visiting the Kapadokya region do not prefer air transport. Ankara Esenboğa (ESB), İzmir Adnan Menderes (ADB) and Muğla Dalaman (DLM) airports have been found to have high operational productivity throughout the entire period. This situation is thought to stem from the fact that these airports are located in regions with high population density and developed tourism. Malatya (MLX), Mardin (MQM) and Şanlıurfa (GNV) airports have been found to have low operational productivity. Among the plausible reasons for this situation is the low utilization of air transport in the regions where these airports are located. In terms of operational productivity, Samsun (SZF) and Trabzon (TZX) airports were found to have low productivity. Possible reasons for this situation include the proximity of these airports to ports and the use of sea transport in addition to air transport. It has been observed that Konya Airport (KYA) has low operational productivity. This situation is thought to stem from the high-speed rail lines used between Konya and major cities such as Ankara and Istanbul.

Tab. 5

First group EATWIOS results (Revenue productivity)

	2019		2020		2021		2022		2023		2024	
A	S	R	S	R	S	R	S	R	S	R	S	R
ADA	0,221	6	0,201	6	0,181	6	0,187	6	0,187	6	0,187	7
ESB	0,503	3	0,452	3	0,377	3	0,373	3	0,373	3	0,373	3
AYT	0,998	1	0,993	1	0,995	1	0,997	1	0,997	1	0,997	1
DIY	0,149	10	0,138	10	0,121	10	0,124	10	0,124	10	0,124	10
EZS	0,132	16	0,121	16	0,107	16	0,109	16	0,109	16	0,109	17
ERZ	0,136	14	0,123	14	0,109	14	0,11	14	0,11	14	0,11	14
GZT	0,167	8	0,156	8	0,137	8	0,144	8	0,144	8	0,144	9
ADB	0,606	2	0,515	2	0,498	2	0,476	2	0,476	2	0,476	2
NAV	0,124	20	0,113	20	0,102	20	0,104	20	0,104	20	0,104	20
ASR	0,159	9	0,149	9	0,137	8	0,141	9	0,141	9	0,141	8
KYA	0,137	13	0,125	13	0,112	13	0,114	13	0,114	13	0,114	13

MLX	0,129	17	0,119	17	0,105	18	0,106	18	0,106	17	0,106	16
MQM	0,127	19	0,115	19	0,103	19	0,105	19	0,105	19	0,105	19
DLM	0,313	5	0,301	5	0,262	5	0,282	5	0,282	5	0,282	5
BJV	0,362	4	0,316	4	0,349	4	0,296	4	0,296	4	0,296	4
OGU	0,134	15	0,123	14	0,109	14	0,11	14	0,11	15	0,11	15
SZF	0,146	11	0,133	11	0,118	11	0,119	11	0,119	11	0,119	11
GNV	0,129	17	0,118	18	0,106	17	0,107	17	0,107	18	0,107	18
TZX	0,191	7	0,172	7	0,155	7	0,168	7	0,168	7	0,168	6
VAN	0,139	12	0,129	12	0,114	12	0,115	12	0,115	11	0,115	12

Note: A: Airport; S: Score; R: Rank

Based on Table 5, Antalya (AYT) airport was found to be the airport with the highest revenue productivity among the first group of airports throughout the entire period. This situation is thought to stem from Antalya (AYT) airport's high aviation and non-aviation revenues, which are dependent on the number of flights and passengers. It was observed that Kapadokya (NAV) Airport had the lowest revenue productivity throughout the entire period. Among the possible reasons for this situation, the low aviation and non-aviation revenues of Kapadokya (NAV) Airport can be pointed out.

After evaluating the operational and revenue productivity of first group airports, the operational and revenue productivity of second group airports was examined. The operational and revenue productivity scores and performance rankings for second group airports are shown in Table 6 and Table 7 respectively.

Tab. 6

Second group EATWIOS results (Operational productivity)

	2019		2020		2021		2022		2023		2024	
A	S	R	S	R	S	R	S	R	S	R	S	R
ADF	0,660	11	0,065	10	0,584	12	0,990	2	0,511	22	0,989	5
AJI	0,755	6	0,070	8	0,679	8	0,538	11	0,989	6	0,966	9
MZF	0,509	19	0,049	20	0,469	20	0,365	21	0,718	18	0,674	19
EDO	0,704	9	0,073	7	0,692	7	0,544	10	0,988	7	0,953	10
BAL	0,912	3	0,081	4	0,884	3	0,686	5	0,997	1	0,998	1
BGG	0,485	21	0,051	17	0,491	16	0,385	18	0,750	16	0,708	18
YEI	0,548	16	0,062	12	0,503	14	0,435	14	0,897	11	0,84	14
CKZ	0,561	14	0,051	17	0,482	18	0,425	15	0,793	13	0,748	15
DNZ	0,735	7	0,086	3	0,709	6	0,646	6	0,993	3	0,992	3
ERC	0,801	5	0,08	5	0,753	5	0,634	7	0,991	5	0,987	6
YKO	0,541	17	0,053	15	0,491	16	0,393	17	0,769	14	0,72	16
HTY	0,995	1	0,693	1	0,996	1	0,997	1	0,984	8	0,985	7
IGD	0,558	15	0,054	14	0,525	13	0,444	13	0,885	12	0,85	13
ISE	0,491	20	0,051	17	0,444	21	0,371	20	0,730	17	0,673	20
KCM	0,676	10	0,066	9	0,612	10	0,956	3	0,513	21	0,915	11
KSY	0,935	2	0,100	2	0,939	2	0,87	4	0,958	9	0,994	2

KFS	0,452	22	0,044	22	0,408	22	0,329	22	0,674	20	0,628	22
MSR	0,729	8	0,065	10	0,676	9	0,555	9	0,992	4	0,979	8
SXZ	0,449	23	0,041	23	0,407	23	0,326	23	0,459	23	0,621	23
NOP	0,539	18	0,052	16	0,478	19	0,379	19	0,751	15	0,709	17
VAS	0,829	4	0,079	6	0,793	4	0,634	7	0,995	2	0,991	4
NKT	0,649	12	0,06	13	0,607	11	0,49	12	0,915	10	0,876	12
TEQ	0,633	13	0,047	21	0,493	15	0,411	16	0,714	19	0,655	21

Note: A: Airport; S: Score; R: Rank

Based on Table 6, among the second group of airports in operational terms, Hatay (HTY) airport was found to have the highest productivity in the 2019-2022 period and Batman (BAL) airport in the 2023-2024 period, while Siirt (SXZ) airport was found to have the lowest productivity throughout the entire period. The plausible reasons why Hatay (HTY) and Batman (BAL) airports have the highest productivity, albeit in different periods, may include the fact that these airports are located in cities that are far from major cities such as Ankara and Istanbul, and that there is no high-speed rail transport in these cities. The probable reasons for Siirt (SXZ) airport having the lowest productivity include the low population density of the region where the airport is located, low trade volume and weak tourism potential. Kars Harakani (KSY) airport in all years except 2023, Sivas Nuri Demirağ (VAS) airport in all years except 2022 and 2024, Adıyaman (ADF) and Kahramanmaraş (KCM) airports only in 2022, and Denizli Airport (DNZ) in 2023 and 2024 have been found to have high productivity. It has been observed that the productivity values of Adıyaman (ADF), Hatay (HTY) and Kahramanmaraş (KCM) airports in 2023 fell significantly short of those in 2022. The earthquakes that occurred at the beginning of 2023 may be cited as one of the probable reasons for this situation.

Tab. 7

Second group EATWIOS results (Revenue productivity)

	2019		2020		2021		2022		2023		2024	
A	S	R	S	R	S	R	S	R	S	R	S	R
ADF	0,488	16	0,381	16	0,72	17	0,665	2	0,313	22	0,657	11
AJI	0,572	11	0,422	12	0,868	10	0,359	16	0,667	12	0,628	12
MZF	0,444	18	0,342	19	0,679	19	0,278	20	0,541	18	0,526	20
EDO	0,602	10	0,499	6	0,953	9	0,424	10	0,771	8	0,729	9
BAL	0,770	4	0,555	3	0,998	1	0,461	6	0,949	3	0,965	2
BGG	0,440	19	0,352	17	0,709	18	0,287	19	0,552	16	0,529	17
YEI	0,517	13	0,437	11	0,738	15	0,366	13	0,642	13	0,603	14
CKZ	0,438	20	0,337	21	0,646	20	0,289	18	0,547	17	0,528	18
DNZ	0,966	2	0,823	2	0,997	2	0,653	3	0,993	1	0,957	3
ERC	0,666	6	0,497	7	0,992	5	0,444	9	0,801	7	0,785	7
YKO	0,466	17	0,345	18	0,73	16	0,309	17	0,570	15	0,527	19
HTY	0,999	1	0,978	1	0,991	6	0,998	1	0,975	2	0,993	1
IGD	0,499	15	0,391	15	0,794	12	0,36	15	0,707	11	0,669	10
ISE	0,504	14	0,46	9	0,753	14	0,363	14	0,617	14	0,545	16
KCM	0,534	12	0,410	13	0,790	13	0,622	4	0,332	21	0,584	15

KSY	0,812	3	0,553	4	0,996	3	0,484	5	0,947	4	0,941	4
KFS	0,388	22	0,304	22	0,588	22	0,248	22	0,482	20	0,466	22
MSR	0,654	8	0,471	8	0,989	7	0,402	11	0,829	6	0,801	5
SXZ	0,371	23	0,279	23	0,57	23	0,235	23	0,269	23	0,447	23
NOP	0,436	21	0,338	20	0,638	21	0,266	21	0,496	19	0,475	21
VAS	0,725	5	0,542	5	0,995	4	0,452	7	0,835	5	0,786	6
NKT	0,612	9	0,459	10	0,987	8	0,4	12	0,764	9	0,737	8
TEQ	0,661	7	0,396	14	0,84	11	0,446	8	0,727	10	0,607	13

Note: A: Airport; S: Score; R: Rank

According to Table 7, in terms of revenue productivity, Hatay (HTY) airport had the highest productivity in 2019, 2020, 2022 and 2024, Batman airport in 2021, and Denizli (DNZ) airport in 2023 among the second group of airports. Siirt (SXZ) airport, has had the lowest productivity throughout the entire period. In terms of revenue productivity, it was determined that Kars Harakani (KSY) airport had high productivity in all years except 2022, Sivas Nuri Demirağ (VAS) airport only in 2021, and Adiyaman (ADF) airport only in 2022.

5. CONCLUSION, LIMITATION, AND FUTURE RESEARCH

Evaluating the productivity of airports, which are of vital importance to the air transport sector, is of considerable significance. This study contributes to the literature by examining the operational and revenue productivity of airports operated by the State (DHMI) in Turkey during the pre-pandemic period (2019), the pandemic period (2020-2021), and the post-pandemic period (2022-2024) using the ENTROPY-EATWIOS integrated model. In this study, airports were categorized by passenger numbers in order to conduct a comprehensive assessment of operational and revenue productivity. In this study, airports were divided into two groups based on passenger numbers in order to comprehensive assessment of operational and revenue productivity. In this context, firstly, the level of importance of input and output variables related to airports was determined using the Entropy Method. In the second stage, the operational and revenue productivity of airports was evaluated using the EATWIOS method.

The analysis using the entropy method revealed that, in terms of operational productivity, terminal size is of high importance in the first group of airports, while Non-aeronautical Revenues are of high importance in terms of revenue productivity. This indicates that terminal area size and non-aviation revenues have significant effects on the productivity of first group airports. It has been determined that, in regard to revenue productivity, Non-aeronautical and Aeronautical Revenues are high significance at airports in the second group, while terminal size is high significance in regard to operational productivity. This demonstrates that aviation and non-aviation revenues and terminal size have significant effects on the productivity of second group airports. The findings obtained are consistent with the results of [38], but inconsistent with the results of [20]. This is thought to be due to differences in the periods studied.

According to the findings obtained from the analysis using the EATWIOS method, it was observed that the second group of airports had higher productivity values than the first group of airports in all years except 2020 in terms of operational productivity. Among the probable reasons for the low productivity of second group airports in 2020, it can be noted that during the Covid-19 pandemic, there was a greater volume of cargo transport compared to passenger transport, and a significant portion of this cargo transport was handled by major airports.

In regard to revenue productivity, the second group of airports has consistently demonstrated higher productivity values than the first group throughout the entire period. One plausible reason for this situation may be that the second group of airports produces a greater output relative to the amount of input they possess. In other words, these types of airports handle more passenger and cargo traffic with fewer staff and lower input costs. At airports in the first group, despite handling more passengers and cargo volume, the high number of employees and costs are leading to a decline in productivity.

According to the results of the EATWIOS method, Antalya Airport (AYT) was found to have the highest productivity in terms of both operational and revenue productivity among the first group of airports. Among the possible reasons for this situation are Antalya being the city that attracts the most tourists and Antalya Airport (AYT) having high aviation and non-aviation revenues based on the number of flights and passengers. Among the airports in the first group, it was determined that Kapadokya (NAV) airport has the lowest productivity in terms of both operational and revenue productivity. This situation is thought to stem from tourists visiting the Kapadokya region preferring road transport over air transport. Within the second group of airports, Hatay (HTY), Batman (BAL) and Denizli (DNZ) airports were found to have the highest operational and revenue productivity at different times. Among the possible reasons for this situation are the fact that the cities where these airports are located are far from major cities such as Ankara and Istanbul, and that there is no high-speed rail transport in these cities. Among the second group of airports, Siirt Airport (SXZ) was found to have the lowest operational and revenue productivity throughout the entire period. This situation can be explained by the weak tourism potential of the region where the airport is located, the low volume of trade and the low population density. It has been observed that the operational and revenue productivity values of the first and second group airports for 2020 fell significantly short of the previous year's figures. This situation is thought to stem from the restrictions imposed during the pandemic.

Taking into account the effects of the Covid-19 pandemic, the findings of this study, which examines the operational and revenue productivity of airports operated by the state (DHMI) in Turkey for the 2019-2024 period, have important managerial implications. Firstly, identifying airport productivity levels provides valuable insights into resource utilization and helps managers use available resources more effectively and increase productivity. Secondly, identifying high-productivity airports using the ENTROPY and EATWIOS methods enables the comparison of the most successful applications, thereby facilitating the sharing of information for productivity improvements across the sector. Thirdly, the findings guide investment decisions, enabling managers to prioritize projects that will increase productivity. Fourthly, it emphasizes the importance of building resilience against external shocks by encouraging the development of contingency plans to mitigate unanticipated events in the future. Fifthly, it emphasizes that the increase in productivity depends on cooperation due to the mutual dependency between airports and stakeholders. Sixthly, it helps airport managers identify and mitigate potential threats.

Consequently, this study provides airport managers and authorities with important information regarding the operational and revenue productivity of airports. In view of this information, airport managers can adapt to changing conditions and increase the productivity of airports by making more informed decisions. The competent authorities can increase the productivity of airports by implementing incentive routes (directing certain airlines to airports with low flight numbers) or by increasing public-private partnerships at airports.

Although this study provides valuable information about the operational and revenue productivity of airports operated by the state (DHMI) in Turkey before and after the pandemic, it should be acknowledged that it has certain limitations. The first limitation is that the study

focuses only on airports operated by the state (DHMI) in Turkey. Future studies could compare differences in terms of ownership or regional aspects by expanding the sample to examine airports operated by the private sector or airports located in different countries. Secondly, large-scale airports such as Istanbul IGA (ISL) and Istanbul Sabiha Gökçen (SAW) could not be included in the sample. This is due to the limited availability of data concerning these airports. Thirdly, it is only the operational and revenue productivity of airports that is investigated. This is because data relating to airports is limited. Future research could examine the productivity of airports from multiple perspectives, incorporating environmental and sustainability criteria. Fourthly, productivity measurement varies depending on the input-output variables and the method used. In this regard, future studies applying parametric methods such as Stochastic Frontier Analysis (SFA) to the existing data set may yield more robust results regarding the productivity of the relevant airports.

References

1. ACI. „Covid-19 Report”. Available at: <https://aci.aero/2022/10/06/the-impact-of-covid-19-on-airports-and-the-path-to-recovery/>.
2. Akın N.G. 2025. „Measuring the Performance of Airport Operations in Türkiye with The MPSI Based MABAC Method”. *Journal of Productivity* 59(4): 803-826. DOI: <https://doi.org/10.51551/verimlilik.1647363>.
3. Augustyniak W., Laura López-Torres, Sławomir Kalinowski. 2015. „Performance of Polish regional airports after accessing the European Union: Does liberalization impact on airports’ efficiency?”. *Journal of Air Transport Management* 43: 11-19. DOI: <https://doi.org/10.1016/j.jairtraman.2015.01.001>.
4. Aytakin Ahmet, Fatih Ecer, Selçuk Korucuk, Çağlar Karamaşa. 2022. „Global innovation efficiency assessment of EU member and candidate countries via DEA-EATWIOS multi-criteria methodology”. *Technology in Society* 68: 1-11. DOI: <https://doi.org/10.1016/j.techsoc.2022.101896>.
5. Chang Yu-Chun, Ming-Miin Yu, Po-Chi Chen. 2013. „Evaluating the performance of Chinese airports”. *Journal of Air Transport Management* 31: 19-21. DOI: <https://doi.org/10.1016/j.jairtraman.2012.11.002>.
6. Chen Shih-Pin, Chun-Shao Chen. 2025. „Measuring the efficiency and productivity changes in international airports before and during the COVID-19 pandemic”. *Transport Policy* 167: 78-90. DOI: <https://doi.org/10.1016/J.TRANPOL.2025.02.023>.
7. Chen Ying-Hsiu, Po-Lin Lai. 2019. „Determining the relationship between ownership and technical efficiency by using a dynamic stochastic production frontier approach”. *Journal of Air Transport Management* 75: 61-67. DOI: <https://doi.org/10.1016/j.jairtraman.2018.12.001>.
8. Chen Ying-Hsiu, Po-Lin Lai, Pairach Piboonrungraj. 2017. „The relationship between airport performance and privatisation policy: A nonparametric metafrontier approach”. *Journal of Transport Geography* 62: 229-235. DOI: <https://doi.org/10.1016/j.jtrangeo.2017.06.005>.
9. Choo Yap Yin. 2014. „Factors affecting aeronautical charges at major US airports”. *Transportation Research Part A: Policy and Practice* 62: 54-62. DOI: <https://doi.org/10.1016/j.tra.2014.02.006>.

10. Cifuentes-Faura J., Ursula Faura-Martínez. 2023. „Measuring Spanish airport performance: A bootstrap data envelopment analysis of efficiency”. *Utilities Policy* 80: 1-9. DOI: <https://doi.org/10.1016/j.jup.2022.101457>.
11. DHMİ. „DHMİ Annual Report”. Available at: https://dhmi.gov.tr/Lists/FaaliyetRaporlari/Attachments/21/DHMI_2020_Faaliyet_Raporu.pdf.
12. Domingos Maria Cecília de Farias, Rogéria de Arantes Gomes, Queiroz, Hélio da Silva Queiroz Júnior, Viviane Adriano Falcão. 2025. „Unlocking efficiency and environmental impact: Analyzing concessioned Brazilian airports”. *Journal of Air Transport Management* 124: 1-18. DOI: <https://doi.org/10.1016/j.jairtraman.2025.102754>.
13. Ersoy Y. 2021. „Performance Evaluation of Airports During the COVID-19 Pandemic”. *Gospodarka Narodowa* 308(4): 23-53. DOI: <https://doi.org/10.33119/gn/143335>.
14. Georges Assaf A., David Gillen. 2012. „Measuring the joint impact of governance form and economic regulation on airport efficiency”. *European Journal of Operational Research* 220(1): 187-198. DOI: <https://doi.org/10.1016/j.ejor.2012.01.038>.
15. Görçün Ö. F. 2019. „Productivity Analysis of Black Sea Container Ports by Using Integrated Entropy and EATWOS Methods”. *Eskişehir Osmangazi University Journal of Economics and Administrative Sciences* 14(3): 811-830. DOI: <https://doi.org/10.17153/oguiibf.511602>.
16. Görçün Ö. F. 2021. „Efficiency analysis of Black Sea container seaports: application of an integrated MCDM approach”. *Maritime Policy and Management* 48(5): 672-699. DOI: <https://doi.org/10.1080/03088839.2020.1783467>.
17. Gudmundsson S. V., M. Cattaneo, R. Redondi. 2021. „Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19”. *Journal of Air Transport Management* 91: 1-8. DOI: <https://doi.org/10.1016/j.jairtraman.2020.102007>.
18. Güner Samet, Jorge Junio Moreira Antunes, Keziban Seçkin Codal, Peter Wanke. 2024. „Network centrality driven airport efficiency: A weight-restricted network DEA”. *Journal of Air Transport Management* 116: 1-15. DOI: <https://doi.org/10.1016/j.jairtraman.2024.102551>.
19. Güner Samet, Erman Coşkun. 2019. „Estimating the operational and service efficiency of bus transit routes using a non-radial DEA approach”. *EURO Journal on Transportation and Logistics* 8(3): 249-268. DOI: <https://doi.org/10.1007/s13676-018-0123-1>.
20. Güner Samet, Keziban Seçkin Codal. 2022. „Endogenous and exogenous sources of efficiency in the management of Turkish airports”. *Utilities Policy* 76: 1-12. DOI: <https://doi.org/10.1016/j.jup.2022.101370>.
21. Güner Samet, Keziban Seçkin Codal. 2024. „Airport productivity and network centrality in the pandemic outbreak: Lessons from the Turkish airports”. *Journal of Air Transport Management* 115: 1-10. DOI: <https://doi.org/10.1016/j.jairtraman.2024.102552>.
22. Jo A. H., Y. T. Chang. 2023. „The effect of airport efficiency on air traffic, using DEA and multilateral resistance terms gravity models”. *Journal of Air Transport Management* 108: 1-11. DOI: <https://doi.org/10.1016/j.jairtraman.2023.102364>.

23. Kaya Gizem, Umut Aydın, Melis Almula Karadayı, Füsün Ülengin, Burç Ülengin, Ayhan İçken. 2022. „Integrated methodology for evaluating the efficiency of airports: A case study in Turkey”. *Transport Policy* 127: 31-47. DOI: <https://doi.org/10.1016/j.tranpol.2022.08.010>.
24. Keskin Burak, Can Deniz Köksal. 2019. „A hybrid AHP/DEA-AR model for measuring and comparing the efficiency of airports”. *International Journal of Productivity and Performance Management* 68(3): 524-541. DOI: <https://doi.org/10.1108/IJPPM-02-2018-0043>.
25. Kiracı K., Cemal Durmuşçelebi. 2022. „Analysis of Airport Performance in Turkey with CRITIC-based EDAS Method”. *Anemon Muş Alparslan University Journal of Social Sciences* 10(2): 837-856. DOI: <https://doi.org/10.18506/anemon.964827>.
26. Lai P. L., A. Potter, M. Beynon, A. Beresford. 2015. „Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique”. *Transport Policy* 42: 75-85. DOI: <https://doi.org/10.1016/j.tranpol.2015.04.008>.
27. Li Y., Q. Cui. 2018. „Airline efficiency with optimal employee allocation: An Input-shared Network Range Adjusted Measure”. *Journal of Air Transport Management* 73: 150-162. DOI: <https://doi.org/10.1016/j.jairtraman.2018.09.002>.
28. lo Storto C. 2018. „Ownership structure and the technical, cost, and revenue efficiency of Italian airports”. *Utilities Policy* 50: 175-193. DOI: <https://doi.org/10.1016/j.jup.2018.01.003>.
29. Oum T., A. Zhang, Y. Zhang. 2004. „Alternative Forms of Economic Regulation and their Efficiency Implications for Airports”. *Journal of Transport Economics and Policy* 38(2): 217-246. DOI: <https://www.jstor.org/stable/20173054>.
30. Oum T. H., N. Adler, C. Yu. 2006. „Privatization, corporatization, ownership forms and their effects on the performance of the world’s major airports”. *Journal of Air Transport Management* 12(3): 109-121. DOI: <https://doi.org/10.1016/j.jairtraman.2005.11.003>.
31. Özsoy Volkan Soner, Hacı Hasan Örcü. 2021. „Structural and operational management of Turkish airports: a bootstrap data envelopment analysis of efficiency”. *Utilities Policy* 69: 1-15. DOI: <https://doi.org/10.1016/j.jup.2021.101180>.
32. Peters M.L., S. Zelewski, A.S. Bruns. 2012. „Extended version of EATWOS concerning satisficing levels for input quantities”. In: *Pioneering Supply Chain Design – A Comprehensive Insight into Emerging Trends, Technologies and Applications*, edited by Blecker T., W. Kersten, C.M. Ringle, 303-318. Germany: Eul Verlag.
33. Shemshadi Ali, Hossein Shirazi, Mehran Toreihi, M. J. Tarokh. 2011. „A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting”. *Expert Systems with Applications* 38(10): 12160-12167. DOI: <https://doi.org/10.1016/j.eswa.2011.03.027>.
34. Sherman H. D., J. Zhu. 2006. „Benchmarking with quality-adjusted DEA (Q-DEA) to seek lower-cost high-quality service: Evidence from a U.S. bank application”. *Annals of Operations Research* 145(1): 301-319. DOI: <https://doi.org/10.1007/s10479-006-0037-4>.
35. Simon H.A. 1979. „Rational decision making in business organizations”. *American Economic Review* 69 (4): 493-513.
36. Song Yonkang, Yanhua Li, Hanchen Ke, Keyan Zhao. 2025. „Study on the subsidy efficiency of small and medium-sized airports in China based on social economic impact”. *Journal of Air Transport Management*, 128. DOI: <https://doi.org/10.1016/j.jairtraman.2025.102852>.

37. Sun X., S. Wandelt, C. Zheng, A. Zhang. 2021. „COVID-19 pandemic and air transportation: Successfully navigating the paper hurricane”. *Journal of Air Transport Management* 94: 1-14. DOI: <https://doi.org/10.1016/j.jairtraman.2021.102062>.
38. Uludağ A. S. 2020. „Measuring the productivity of selected airports in Turkey”. *Transportation Research Part E: Logistics and Transportation Review* 141: 1-31. DOI: <https://doi.org/10.1016/j.tre.2020.102020>.
39. Wang Tien-Chin, Hsien-Da Lee. 2009. „Developing a fuzzy TOPSIS approach based on subjective weights and objective weights”. *Expert Systems with Applications* 36(5): 8980-8985. DOI: <https://doi.org/10.1016/j.eswa.2008.11.035>.
40. Wang Xi, Jie Zheng, Liang(Rebecca) Tang, Yi Luo. 2023. „Recommend or not? The influence of emotions on passengers’ intention of airline recommendation during COVID-19”. *Tourism Management* 95: 1-14. DOI: <https://doi.org/10.1016/j.tourman.2022.104675>.
41. Wang Z., X. Zhu, H. Zhang, A. Boocock. 2023. „Study on non-aeronautical efficiency of Chinese listed airports based on two-stage network DEA”. *Research in Transportation Business and Management* 46: 1-14. DOI: <https://doi.org/10.1016/j.rtbm.2022.100867>.
42. Wanke P. F. 2013. „Physical infrastructure and shipment consolidation efficiency drivers in Brazilian ports: A two-stage network-DEA approach”. *Transport Policy* 29: 145-153. DOI: <https://doi.org/10.1016/j.tranpol.2013.05.004>.
43. Yilmaz M. K., A. O. Kusakci, M. Aksoy, U. Hacıoglu. 2022. „The evaluation of operational efficiencies of Turkish airports: An integrated spherical fuzzy AHP/DEA approach”. *Applied Soft Computing* 119 1-16. DOI: <https://doi.org/10.1016/j.asoc.2022.108620>.
44. Yu M. M., I. Rakshit. 2023. „Assessing the dynamic efficiency and technology gap of airports under different ownerships: A union dynamic NDEA approach”. *Omega (United Kingdom)* 119: 1-17. DOI: <https://doi.org/10.1016/j.omega.2023.102888>.
45. Yüksekıldız E. 2021. „Productivity Analysis of Turkey Container Ports with ENTROPY and EATWOS Methods”. *Journal of Productivity* 2: 3-24. DOI: <https://doi.org/10.51551/verimlilik.660708>.
46. Zhang Hong, Chao-lin Gu, Lu-wen Gu, Yan Zhang. 2011. „The evaluation of tourism destination competitiveness by TOPSIS & information entropy - A case in the Yangtze River Delta of China”. *Tourism Management* 32(2): 443-451. DOI: <https://doi.org/10.1016/j.tourman.2010.02.007>.
47. Zolfani S. H., Ö. F. Görçün, M. Çanakçıoğlu, E. B. Tirkolaei. 2023. „Efficiency analysis technique with input and output satisficing approach based on Type-2 Neutrosophic Fuzzy Sets: A case study of container shipping companies”. *Expert Systems with Applications* 218: 1-21. DOI: <https://doi.org/10.1016/j.eswa.2023.119596>.

Received 16.04.2026; accepted in revised form 05.07.2026



Scientific Journal of Silesian University of Technology. Series Transport is licensed under a Creative Commons Attribution 4.0 International License