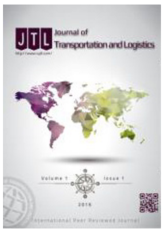

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RESEARCH ARTICLE

Exploring the Sources of Centrality in the Turkish Domestic Airport Network

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ABSTRACT

Air passenger transportation in Turkey has been in rapid development since the mid-1980s due to the increasing investments in infrastructure and deregulating policies. This paper analyzed the network performances of Turkish airports and assessed the evolution from 2012 to 2020, from both topological and spatial perspectives. Unweighted and weighted graphs based on flight frequencies were used to determine airport centrality. Sabiha Gökçen (SAW) was defined as the most central airport in the domestic network and airport centrality showed significant improvement during the observation period. The weighted graph recorded significant losses in the centrality performances of airports, excluding eigenvector, during the pandemic process. Exogenous sources of airport centrality were also examined using Gradient Boosting Modeling. Results demonstrated the importance of the population and economic strength of the city in airport centrality, the decisive role of tourism demand and international flights on betweenness centrality, and the necessity of passenger terminal size on eigenvector centrality.

Keywords: Complex network, Turkish airport system, Airport centrality, Gradient Boosting Modeling

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1. Introduction

Air passenger transportation has increased significantly since the mid-1980s in Turkey due to liberalization policies and growing investments in infrastructure. The Turkish airport system includes fifty-six airports and is one of the region's largest markets for air passenger transport. 839.8 thousand flights were operated and 99.9 million passengers were carried in 2019[1] within the domestic airport network. Despite the increasing role of air transport in Turkey, studies in the literature regarding the spatial and topological characteristics and network performances of Turkish airports are limited.

Kılıç Depren and Gökalp Yavuz (2018) examined the air transport structure of Turkey and assessed inter-country network characteristics (airports, routes, and clustering coefficients) and degree and betweenness centralities. Their results indicated that Istanbul has a huge impact on the air transport network and Germany and Cyprus have the largest connection with Turkey. The authors also emphasized that the degree centrality values decline exponentially with one or two dominant airports, while betweenness has a power distribution. Moreover, a high correlation was found between centrality and passenger volume. Erdem et al. (2019) examined the topology of the air transport network in Turkey based on passenger, flight, and cargo flows. The average degree, clustering coefficient, average clustering coefficient, modularity, average path length, and graph density were considered as measures of network topology. The authors found that the Turkish aviation industry is heavily dependent on passenger transport. The airports of Istanbul, Ankara, Izmir, and Antalya located in the western part were more connected than the eastern part based on passenger and cargo flow.

The current paper intends to improve the literature by studying the topological, temporal, and spatial aspects of Turkish airport centrality. Unlike the previous research, this paper examines the evolution of Turkish airport centrality between 2012 and 2020, thus aiming to capture temporal changes in the network. The airport-level centrality was examined with unweighted and weighted graphs based on flight frequencies. The experiment provided substantial support to our main idea, that is, spatial network structure based on the weighted graph is more successful in capturing the temporal and geographic evolution of the airport network and was able to explain the impact of macro-environmental factors such as the Covid 19 pandemic.

The exogenous sources of airport centrality at the domestic level were also addressed in this paper. As demonstrated by many previous researches, contextual variables such as macro-environmental factors, governance and ownership structure, geographical location, and competition have a strong impact on the operational performances of airports (Chi-Lok and Zhang, 2009; Wanke, 2013; Chaouk et al. 2020). However, only limited research in the literature examined the impact of exogenous contextual variables on the network performance of airports. Wang et al. (2011) found a strong correlation between the centrality indices of Chinese airports with population, gross regional domestic product, and passenger volumes of the cities. Lin (2012) discussed the impact of the tourism industry

1 These figures were dramatically decreased to 572.9 thousand flights and 49.7 million passengers in 2020 because of the coronavirus pandemic.

and competition among transportation modes on separate distance flights. Wandelt and Sun (2015) investigated the impact of various contextual variables (population, area, GNI per capita, life expectancy at birth) on topologic and functional criticality measures and found a strong correlation between a country's GDP and airport centrality.

The current paper considered various contextual variables and assessed their impact on the network performances of Turkish airports using Gradient Boosting Modeling. Therefore, we explored the key exogenous properties that provide stronger connections to hub airports in the domestic networks. Consistent with the literature, we found the positive effects of population and economic development on airport centrality. Also, we revealed the decisive impact of foreign tourist mobility and the percentage of international flights on betweenness centrality. Results also demonstrated the importance of passenger terminal size on eigenvector centrality.

In summary, this paper aims to answer three questions: 1) how has the domestic centrality of Turkish airports changed during the observation period?, 2) how has the Covid-19 pandemic affected airport centrality?, 3) what are the factors affecting airport centrality? The answers to these questions are important in determining the importance and position of each airport in the domestic network. Thus, critical hubs within the network can be identified and the basis for further analysis to measure the robustness of the network can be established. Moreover, determining the factors affecting centrality will reveal the necessary conditions for airports to have a stronger hub position.

The paper is organized as follows. Section 2 outlines the methodology of the research. Section 3 presents the findings, and Section 4 offers a conclusion.

2. Methodology

This research attempts to capture the temporal and spatial evolution of Turkish airport centrality by highlighting the impacts of macro-environmental changes and demonstrating the importance of exogenous sources for airport centrality. Using data from the Turkish domestic airport system, the network performance will be assessed in the first stage by utilizing centrality measures. The exogenous sources of airport centrality were explored in the second stage using Gradient Boosting Modeling.

2.1. Data

From January 2012 to December 2020, this research covers Turkish airports serving the domestic network. The number of airports was 49 at the end of 2011. However, it changed during the observation period due to new airports and temporary closures. Six new airports were opened (BGG, NKT, KFS, YKO, OGU, and IST), whereas one airport was permanently closed (ISL). Several airports (USQ, NOP, GKD, BZI, and TJK) were temporarily shuttered and subsequently reopened during this period, while others temporarily suspended domestic flights (ISE and ONQ). Due to a lack of commercial aviation traffic, CII was never included in the analysis. According to current data, the view of the domestic air transportation network in Turkey is shown in Figure 1. The data gathered from DHMI (General Directorate of State Airports Authority) contains the routes and the number of direct flights from airport i to airport j within the domestic network. Graphs are a type of data and display airports and their connections to be modeled and analyzed. The unweighted graph considers basic connectivity and equalizes all relationships to 1 when the flight occurs, otherwise it is 0. The weighted graph tracks the number of flights between two airports.

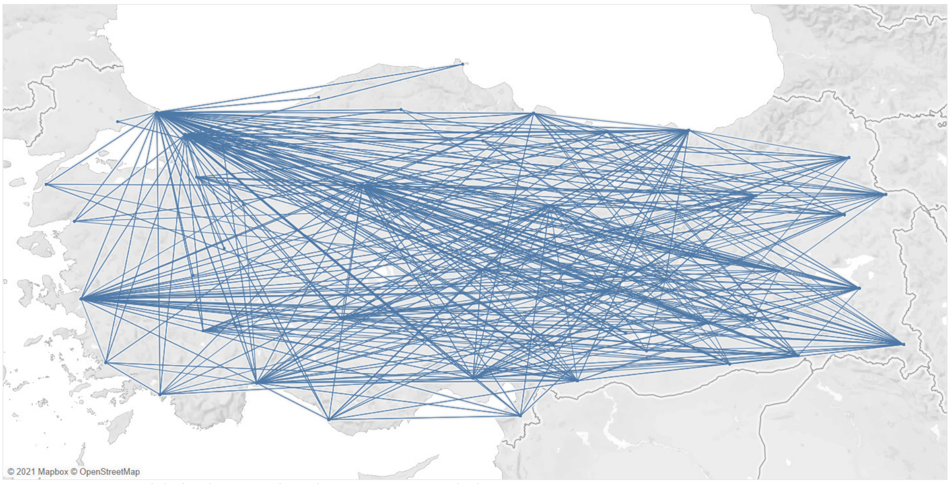

Figure 1. Turkish domestic airport network in 2020

2.2. Centrality Measures

The centralization is possessed by the center of a network (Freeman, 1978) and it is important to assess the hub potential of a node, identify travel decisions in a network, and measure the system's performance based on unit-level (Wellman and Leighton, 1979; Li et al., 2021). Degree centrality, betweenness centrality, and eigenvector centrality measures were used in this study to assess the centrality performance of each airport.

Degree Centrality (DC): The degree of a node simply refers to the number of edges (connections or links) it has. Degree centrality measures the total number of edges connected to a particular node and refers to local connectivity (Cats and Krishnakumari, 2020). A higher degree centrality shows higher local connectivity and indicates the hub potential of an airport in the network. The degree centrality of i^{th} airport can be measured by Eq. 1:

$$DC_i = \sum_{j=1}^{n} a_{ij} \quad (1)$$

The degree centrality can be distinguished into in-degree and out-degree. The former refers to the number of edges connecting from other nodes to node i. The latter refers to the number of edges connected from node i to other nodes. Both measures are useful to capture the frequency of travel paths in a transportation network.

Betweenness Centrality (BC): Betweenness centrality refers to how much a given node is in-between others (Perez and Germon, 2016) and is defined as a transit point along the shortest geodesic path between two other airports in the network (Freeman, 1978). As Wang et al. (2011) discussed, a node will be more impactful if it is located on the shortest paths connecting many other node pairs. In airport practice, this measure can be interpreted as a transit point along the shortest geodesic path between two other airports in the network. The betweenness centrality of i^{th} airport can be measured by Eq. 2:

$$BC_i = \sum_{st} \frac{n_{st}^i}{g_{st}} \quad (2)$$

where n^i_{st} is the number of geodesic paths from node S to t that pass through node i and g_{st} is the total number of geodesic paths from node S to t.

Eigenvector Centrality (EC): Eigenvector centrality is an extended type of degree centrality and considers both the number of neighbors of a node in the network and the centrality properties of these neighbors. Hence, this measure quantifies the impact of the centrality of neighbors (Kosorukoff, 2011) and depicts the strength of a connection. Thus, the higher eigenvector centrality value indicates that the airport is linked to hub airports and has a strong connection. The eigenvector centrality of i^{th} airport can be measured by Eq. 3:

$$EC_i = \frac{1}{\lambda} \sum_{j=1}^{n} a_{ij} x_j \quad (3)$$

where λ refers a constant value and a_{ij} is an element of the adjacency matrix and x is the vector with elements x_j. There will be many different eigenvalues λ lambda for which a non-zero eigenvector solution exists. However, the requisite related to all the entries in the eigenvector be non-negative refers that only the greatest eigenvalue results in the desired centrality measure (Newman, 2008).

2.3. Gradient Boosting Modeling

As a machine learning approach, gradient boosting is an efficient tool for solving regression and classification tasks. The prediction of gradient boosting modeling is built in a stage-wise fashion. A general gradient boosting architecture has developed for addictive regression models through the perspective of numerical optimization in function space (Friedman, 2001). The model update is computed by sequentially fitting a simple parameterized function with current pseudo-residuals using least squares at each iteration (Friedman, 1999). In function estimation, a regression function is generated, $f(x)$, that minimizes the expectation of some loss function, $\psi(y, f)$,as shown in iterations. Initialize $\hat{f}(x)$ to be constant, $\hat{f}(x) = argmin_p \Sigma_{i=1}^{N} \psi(y_i, p)$. For t in 1, …, T do (Ridgeway, 2012)

1. Compute the negative gradient as the working response

$$z_i = \frac{\partial}{\partial f(x_i)} \psi(y_i, f(x_i))|_{f(x_i)=\hat{f}(x_i)} \quad (4)$$

2. Fit a regression model, $g(x)$, predicting Z_i from the covariates X_i

3. Choose a gradient descent step size as

$$\rho = arg \min_{\rho} \sum_{i=1}^{N} \psi f\left(y_i, \hat{f}(x_i) + \rho g(x_i)\right) (5)$$

4. Update the estimate of $f(x)$ as

$$\hat{f} \leftarrow \hat{f}(x) + \rho g(x) (6)$$

Gradient boosting of regression models results in processes that are competitive, highly robust, and interpretable. Besides, Friedman (2001) has also developed an extension of a variable's relative influence for boosted estimates. The relative influence of a variable x_j is

$$\hat{J}_j^2 = \sum_{splitsonx_j} I_t^2 \ (7)$$

where I^2_t is the empirical improvement by splitting on x^2 at that point. As a partial justification, I^2 can be interpreted by the relevance of the predictor variable x_j (Friedman, 2001).

Gradient Boosting can provide fast and reliable models for many engineering simulations and also find the optimal variables of a defined objective function. There are many publications that focus on predicting future trends based on gradient boosting as a machine-learning model. Dahiya, Saini and Chalak (2021) estimate the time period of the irregular precast concrete structural system with cross bracing using gradient boosting-based regression modeling. There are also studies that use gradient boosting for forecasting the impact of climate change (Cai, Wei, Xu, & Ding, 2021; Cheng et al., 2021) and energy prediction (Qiu et al., 2022). In addition, some scholars concentrate on the comparison of the performance of the machine learning models (Dyer et al., 2022) and develop a hybrid model using gradient boosting (Zhou, Fujita, Ding, & Ma, 2021).

Gradient Boosting can optimize different loss functions and provide several hyper parameter-tuning options that make the function fit very flexible. On the other hand, GBMs can be time and memory exhaustive and can also over-emphasize outliers and cause over-fitting. Using cross-validation to neutralize the over-fitting is suggested.

3. Findings

3.1. Airport-Level Centrality

Centrality analyses provide a snapshot of the network at a single time. That is, how many routes an airport has and which airports are most central and serve as a hub in the network (Newman, 2010). Table 1 displays the main characteristics of the Turkish airport network, including the number of airports, the number of edges (flight routes), and centrality measures. The number of active airports increased from 2012 to 2020, since some airports were temporarily closed and then reopened. The total number of routes has increased steadily and significantly except in 2018. Currently, 51 airports have 580 routes covering the dyadic and unique edge. From an airport management point of view, this demonstrates the improved accessibility in the system.

The overall changes in the centrality values from 2012 to 2020 provide important insights into the evolution of the Turkish airport system. Approximately 43% of airports had fewer than five destinations in 2012. This rate dropped to 30% in 2020. Thus, the number of destinations has increased. The accessibility of airports has also improved during the same period. While 32% of airports could be accessed from less than only five departure points in 2012, this rate decreased to 20% in 2020.

The unweighted graphs exhibit the topological characteristics of the network, and the weighted graphs consider the flight frequencies (Table 2). The unweighted graph indicates an increased performance on the average values of each centrality indicator. In the weighted graph, averages of degree centrality and eigenvector regularly increased until 2018, but decreases were recorded after this year. The averages of betweenness showed irregular patterns both in the weighted and unweighted graphs.

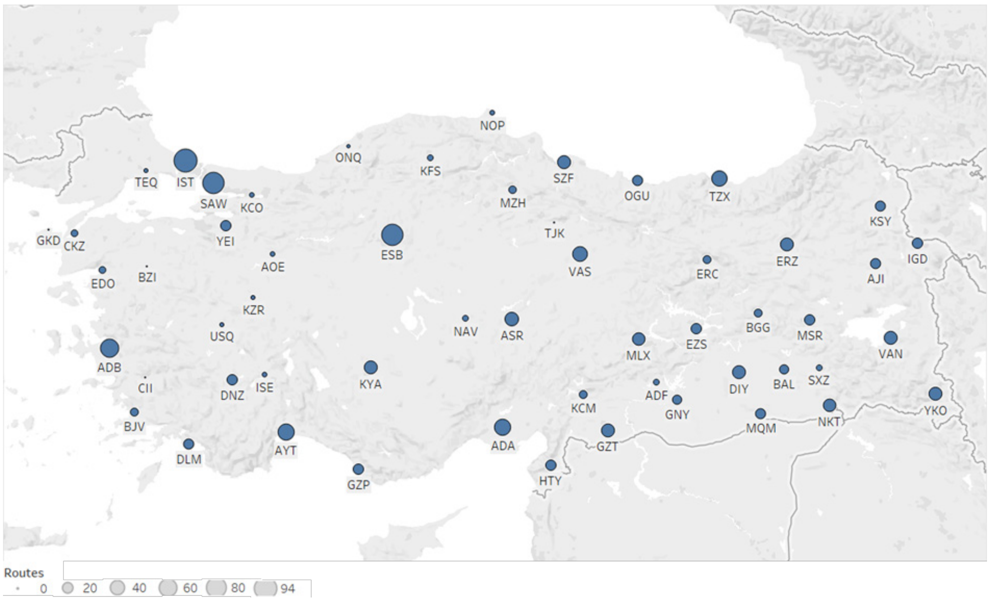

Figure 2. Distribution of degree centralities in 2020

Airport-specific in-degree values showed that the airports in Istanbul (SAW, ISL, and IST) are the most popular destinations in domestic flights both in unweighted and weighted graphs. Readers should recall that ISL was closed in May 2019, and all operations were moved to IST. These airports also had the highest out-degree connections during the observation period except in 2012. Figure 2 shows the degree centralities of airports as of 2020. Please note that this figure displays the total number of connections of each airport and does not present the flight frequency. As can be seen from the figure, ESB, ADB, AYT, TZX, ADA, and VAS are other airports with high degrees. It has also been observed that although the airport density is high in the southeast part of the country, the degrees of the airports in this region are relatively low.

Similar to degree centrality, airports in Istanbul yielded the highest eigenvector centrality scores both in unweighted and weighted graphs. SAW received the highest eigenvector centrality score from 2012 to 2016 in the unweighted graph, while ISL and IST received the highest score from 2017 to 2020. In the weighted graph, however, ISL yielded the maximum eigenvector centrality score in the early years of observation, while SAW has come to the fore since 2016. 2016 is a breaking point; because, for the first time, the number of domestic flights operated from/to SAW exceeded those from ISL.

Nearly 35% of airports received a betweenness value of zero in 2012, which indicates that a significant proportion of the sample had no shortest routes between other city pairs. This rate decreased to 13.7% in 2020. The average betweenness has an inconsistent trend and peaked in 2019. Although this value is lower in 2020, it is still greater than in earlier periods. This suggests that there were more transit points during the outbreak era. Similar to other centrality measures, airports of Istanbul (SAW, IST, and ISL) yielded the maximum betweenness centrality scores in the unweighted graph.

Table 1: Unweighted Graph for Network Centrality

		2012	2013	2014	2015	2016	2017	2018	2019	2020
Airports		47	50	50	52	51	50	50	52	51
Flight Routes		428	535	542	553	545	548	540	578	580
In-degree	Max	40 (SAW)	42 (SAW)	45 (ISL)	46 (SAW)	45 (SAW, ISL)	46 (ISL)	45 (ISL)	47 (IST, ISL)	46 (IST)
	Avg.	9.106	10.7	10.84	10.634	10.686	10.96	10.8	11.115	11.372
Out-degree	Max	39 (ESB)	43 (SAW)	46 (SAW)	45 (SAW)	44 (SAW)	44 (ISL)	45 (ISL)	48 (IST)	46 (IST)
	Avg.	9.106	10.7	10.84	10.634	10.686	10.96	10.8	11.115	11.372
Betweenness	Max	523.003 (ESB)	597.867 (SAW)	564.835 (SAW)	655.645 (SAW)	596.324 (SAW)	537.405 (ISL)	573.862 (ISL)	624.905 (IST)	766.250 (IST)
	Avg.	38.191	39.5	39.04	41.615	40.313	39.04	39.28	40.730	40.333
Eigenvector	Max	1.00 (SAW)	1.00 (SAW)	1.00 (SAW)	1.00 (SAW)	1.00 (SAW)	1.00 (ISL)	1.00 (ISL)	1.00 (ISL)	1.00 (IST)
	Avg.	0.363	0.379	0.372	0.363	0.367	0.366	0.371	0.377	0.381

Table 2: Weighted Graph for Network Centrality

		2012	2013	2014	2015	2016	2017	2018	2019	2020
In-degree	Max	114753 (ISL)	126530 (ISL)	133020 (ISL)	132697 (ISL)	139878 (SAW)	134215 (SAW)	141203 (SAW)	132133 (SAW)	81174 (SAW)
	Avg.	10285.85	11083.32	12121.24	12861.87	13709.14	14243.6	14369.64	11991.92	7023.588
Out-degree	Max	114734 (ISL)	126520 (ISL)	132865 (ISL)	132846 (ISL)	140220 (SAW)	134300 (SAW)	141222 (SAW)	132111 (SAW)	81444 (SAW)
	Avg.	10285.85	11083.32	12121.24	12861.87	13709.14	14243.6	14369.64	11991.92	7023.588
Betweenness	Max	610.783 (AYT)	516.10 (AYT)	842.864 (AYT)	686.711 (KCO)	578.466 (AYT)	457.284 (AYT)	593.906 (AYT)	1186.252 (AYT)	495.00 (SAW)
	Avg.	113.013	109.184	110.456	107.888	121.058	111.904	113.421	140.865	119.570
Eigenvector	Max	1.00 (ISL)	1.00 (ISL)	1.00 (ISL)	1.00 (ISL)	1.00 (SAW)	1.00 (SAW)	1.00 (SAW)	1.00 (SAW)	1.00 (SAW)
	Avg.	0.133	0.133	0.142	0.150	0.157	0.167	0.159	0.136	0.143

The top ten most central airports for unweighted and weighted graphs are listed in Tables 3 and 4. The list has not changed significantly from 2012 to 2020. ESB, operating in the capital city, was ranked at the top in 2012 and just followed the airports in Istanbul in the remaining years. Remarkably, some airports with high degree and eigenvector centrality scores did not list in the betweenness centrality (ESB, ADB, GZT, BJV, DIY) of the weighted graph. This finding is consistent with Wang et al. (2011), who found that airports with a high degree centrality do not necessarily receive high betweenness scores. The hub airports with high degree and eigenvector received relatively low betweenness centrality scores. AYT, which is the main tourist destination, received the highest betweenness score in most years.

Table 3: Most central airports (unweighted graph)

Rank	In-degree		Out-degree		Betweenness		Eigenvector	
	2012	2020	2012	2020	2012	2020	2012	2020
1	SAW	IST	ESB	IST	ESB	IST	SAW	IST
2	ESB	SAW	SAW	SAW	SAW	SAW	ESB	ESB
3	ISL	ESB	ISL	ESB	ISL	ESB	ISL	SAW
4	AYT	ADB	AYT	ADB	AYT	ADB	AYT	ADB
5	ADB	ADA	ADB	VAS	ADB	AYT	ADB	AYT
6	TZX	AYT	ERZ	AYT	TZX	TZX	TZX	ADA
7	ADA	TZX	ADA	TZX	ADA	ADA	ADA	TZX
8	ASR	GZT	TZX	ADA	ERZ	SZF	ASR	VAS
9	YEI	ERZ, VAN	EZS	ASR	YEI	VAS	GZT	ASR
10	GZT	NKT	ASR	KYA	SZF	ERZ	ERZ	KYA

Table 4: Most central airports (weighted graph)

Rank	In-degree		Out-degree		Betweenness		Eigenvector	
	2012	2020	2012	2020	2012	2020	2012	2020
1	ISL	SAW	ISL	SAW	AYT	SAW	ISL	SAW
2	SAW	IST	SAW	IST	ERZ	ERZ	ADB	ADB
3	ESB	ESB	ESB	ESB	SAW	TZX	ESB	IST
4	ADB	ADB	ADB	ADB	YEI	ADA	SAW	ESB
5	AYT	AYT	AYT	AYT	DNZ	KFS	AYT	AYT
6	ADA	ADA	ADA	ADA	KYA	IST	ADA	ADA
7	TZX	TZX	TZX	TZX	ADA	AYT	TZX	TZX
8	BJV	GZT	BJV	GZT	GZT	SZF	BJX	GZT
9	GZT	BJV	GZT	BJV	ESB	VAS	GZT	BJV
10	DIY	DIY	DIY	DIY	EZS	ASR	DIY	ASR

Considering all centrality measures, IST appears to be topologically the most central airport of the domestic network as of 2020. However, SAW has been the most central domestic airport recently when the numbers of flights are taken into account. ESB, ADB, AYT, ADA, TZX, VAS, GZT, and ASR appeared to be the other hubs in the Turkish domestic air transport system based on node-level centrality. Besides, the weighted graph clearly exhibits the temporal and seasonal effects, geographical condition change, and more. The tourism centers, financial centers, and regions with high population density can also be specified in the weighted graph. Meanwhile, the permanent impact of the Covid-19 pandemic outbreak on the aviation network has been observed in the weighted graph.

Unweighted and weighted graphs produced quite different results for airport-level centrality, where the topological perspective based on the unweighted graph could not capture the temporal changes specific to the pandemic period. The weighted graph, on the other hand, successfully explained the changes in the airport network during the pandemic period and revealed the losses in in-degree, out-degree, and eigenvector centrality. Indeed, as Table 3 shows, the values of these metrics gradually decreased during the pandemic. Betweenness centrality peaked in 2019 but dropped again in 2020. Still, the average betweenness centrality is slightly higher compared to pre-pandemic, indicating increased transit points.

3.2. Sources for Airport Centrality

The spatial characteristics of the geographical area can significantly affect airport centrality. As demonstrated in previous studies, economic development (Wang et al. 2011; Wandelt and Sun, 2015), population (Wang et al., 2011), tourism demand, and competition among transportation modes (Lin, 2012) can improve the centrality of an airport. In the current paper, the impacts of nine contextual variables on Turkish domestic airport centrality were examined using Gradient Boosting Modeling: population of the city, socio-economic development index (SEDI) and human development index (HDI) of the city, terminal size (m2) of the airport, the annual number of citizen and foreign tourists hosted in the city, percentage of international flights, nearest airport (km), and distance to the city center (km). The results are presented in Table 5. The coefficients in the table show the relative influence of each contextual variable on weighted centrality measures. The nearest airport and distance to the city center as contextual variables do not have an empirical improvement on weighted centrality measures, which have no value in Table 5.

Table 5: Relative influences of contextual variables on weighted centrality measures

Variables	In-degree	Out-degree	Betweenness	Eigenvector
Population	59.552	57.237	67.512	28.255
SEDI	36.573	37.854	3.962	19.860
Terminal size	3.469	3.471	-	47.364
Citizen tourist	0.406	0.406	11.402	4.521
Foreign tourist	-	-	13.107	-
HDI	-	1.032	-	-
Percentage of international flights	-	-	4.016952	-
Nearest airport	-	-	-	-
Distance to the city center	-	-	-	-

The results demonstrated the different drivers of each centrality metric in the Turkish domestic airport network. In-degree and out-degree centralities are affected by similar contextual variables. The city's population is the most decisive attribute and the socio-economic development of the population is the second major source. This finding supports Wang et al. (2011) and Wandelt and Sun (2015), who highlighted the importance of population and economic power for airport centrality. The size of the terminal area and the number of citizen tourists are relatively less effective on in-degree and out-degree centralities where the number of foreign tourists has no impact. This finding was expected since the domestic network was examined in this study. Unlike in-degree, the out-degree centrality is barely affected by the human development index of the city.

Similar to in-degree and out-degree, the city's population is the major source of betweenness centrality. The numbers of both citizens and foreign tourists are more important for betweenness centrality than other centrality metrics. While the percentage of international flights improves the betweenness centrality, SEDI is much less effective. This finding demonstrates the importance of tourism demand of the region (particularly the foreign tourists) and international flights for an airport to have control over the connections in the network and serve as a transshipment point. The drivers of the eigenvector centrality are much different. The size of the terminal area is the most important driver for eigenvector centrality and is followed by population and SEDI, where the impact of citizen tourists is minimal. Eigenvector centrality in air transportation is associated with connections to high-scoring airports, such as hubs, that are contributed by accessibility via more frequent flights to a wider range of destinations. Larger terminal size allows for more gates and improved facilities and can facilitate access to hubs, resulting in high eigenvector centrality.

4. Conclusion

This research examined the temporal and spatial evolution of the airport network and demonstrated the importance of exogenous sources for airport centrality. The network performances of Turkish domestic airports were assessed by centrality measures. In addition to unweighted topological assessments, weighted analysis was also performed based on the flight frequencies.

The results indicated the most and least central airports and highlighted the temporal changes during the observation period. Sabiha Gökçen (SAW) is the most central airport in the domestic network. IST, ESB, ADB, AYT, and ADA are the airports with the most domestic connections. Erzurum (ERZ), Trabzon (TZX), Adana (ADA), Kastamonu (KFS), and Istanbul (IST) are the important hubs that connect the most airports in the domestic network. Furthermore, Adnan Menderes (ADB), Istanbul (IST), Esenboğa (ESB), and Antalya (AYT) were identified as the airports with the strongest connections.

The average in-degree and out-degree centrality increased steadily until 2018. The degree values decreased in 2019 due to the contraction in the domestic passenger market. Due to the Covid-19 pandemic, the weighted degrees dramatically reduced in 2020. The average betweenness followed an irregular course and reached a peak in 2019. Although it decreased significantly in 2020, it is still higher than in previous periods. This indicates increased transit points during the pandemic period. Here, we observed that the topological perspective of the unweighted graph failed to explain the real impact of the pandemic on the Turkish airport network. Therefore, we concluded that the weighted graph is more useful for capturing the temporal and spatial evolution of the airport network by highlighting the impacts of macro-environmental changes, such as the pandemic outbreak, and produced more robust results than the unweighted graph.

The exogenous sources of airport centrality at the domestic level were investigated using Gradient Boosting Modeling. The results demonstrated the importance of the population and economic strength of the city on degree centrality, and the decisive roles of tourism demand (mainly the foreign tourists) and international flights on betweenness centrality. This demonstrates the importance of location advantage for airport centrality. For eigenvector centrality, the size of the passenger terminal seems to be more important than others, which implies the importance of infrastructure on access to the main hubs in the domestic network.

Finally, a suggestion for future studies will be presented. In the literature, the robustness of the airport network structures in the face of unexpected events (such as random failures and terrorist attacks) has been extensively analyzed (Lordan et al., 2014; Chen et al., 2020; Sun and Wandelt, 2021). However, such a study has not yet been conducted for the Turkish airport system. Further studies can address this issue and analyze the impact of a hub airport's temporary closure on the overall network, define the most critical airports, and provide recovery suggestions.

Appendix: Airports with IATA codes

Airport	IATA	Airport	IATA	Airport	IATA
İstanbul Atatürk	ISL	Batman	BAL	Konya	KYA
İstanbul	IST	Bingöl	BGG	Malatya	MLX
İstanbul Sabiha Gökçen	SAW	Bursa Yenişehir	YEI	Mardin	MQM
Ankara Esenboğa	ESB	Çanakkale	CKZ	Muş Sultan Alparslan	MSR
İzmir Adnan Menderes	ADB	Çanakkale Gökçeada	GKD	Kapadokya	NAV
Antalya	AYT	Denizli Çardak	DNZ	Ordu-Giresun	OGU
Gazipaşa Alanya	GZP	Diyarbakır	DIY	Samsun Çarşamba	SZF
Muğla Dalaman	DLM	Elazığ	EZS	Siirt	SXZ
Muğla Milas-Bodrum	BJV	Erzincan	ERC	Sinop	NOP
Adana	ADA	Eskişehir Hasan Polatkan	AOE	Sivas Nuri Demirağ	VAS
Trabzon	TZX	Hakkâri Yüksekova Selahaddin Eyyubi	YKO	Şanlıurfa GAP	GNY
Erzurum	ERZ	Hatay	HTY	Şırnak Şerafettin Elçi	NKT
Gaziantep	GZT	Iğdır Şehit Bülent Aydın	IGD	Tekirdağ Çorlu Atatürk	TEQ
Adıyaman	ADF	Isparta Süleyman Demirel	ISE	Tokat	TJK
Ağrı Ahmed-i Hani	AJI	Kahramanmaraş	KCM	Uşak	USQ
Amasya Merzifon	MZH	Kars Harakani	KSY	Van Ferit Melen	VAN
Aydın Çıldır	CII	Kastamonu	KFS	Zafer	KZR
Balıkesir Koca Seyit	EDO	Kayseri	ASR	Zonguldak Çaycuma	ONQ
Balıkesir Merkez	BZI	Kocaeli Cengiz Topel	KCO		

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