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An Air Traffic Rebound Comparison Between Romania and the European Union: A Post-Pandemic Scenario of Boarding-Time Minimization Potential

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Abstract

This research offers a comprehensive inspection of the Romanian air transportation domain inside the European Union using existing academic papers in order to perform an experimental analysis of boarding time and cost minimization and to estimate the gross experimental monetary economization. A total of three purposes are defined for the analysis: defining a comparative investigation of a total of 23 European Union countries for 2025 data extracted from Eurostat, excluding France, Estonia, Malta and Belgium due to the lack of data; performing a national and airport-level analysis for the Romanian air transportation sector using Romanian Airport Association observations; and extracting the passenger downfall for 2020–2022 period caused by the COVID-19 pandemic for all 27 countries from the European Union. At the same time, a presentation of the immediate impact of the COVID-19 pandemic was calculated by comparing the 2020 passenger values compared to those from 2019, besides a cumulative impact of the 2020–2022 period compared to the 2019 values. Romania, for instance, registered a downfall of 69.1% in 2020 compared to 2019. A total of five boarding techniques extracted from the academic community were tested in order to identify the optimum method from a theoretical perspective and the most feasible one to be implemented by airline companies. According to the outcomes, the assigned-seat technique saves the most cost and time, but the feasibility level is very limited, due to the difficulties in implementation and communicating to the passengers, while WILMA stands as the most feasible method, but it does not save a similar amount of time and costs. The calculated monetary values stand as gross theoretical amounts instead of realized savings of air transportation companies, and their practical potential should be demonstrated by validating the outcomes on flight-level data and if boarding procedures rely on the critical turnaround path.

Keywords: Romania; air transportation recovery; airplane boarding; potential savings on boarding-related cost; European Union; passenger traffic

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1. Introduction

The air transportation sector contributes to national and regional economic development and connectivity by allowing for population mobility, access and tourism to spread into multiple markets. Based on historical scientific papers, there is a link between regional

economic development and the availability of air transportation, while the impact depends on one market or region or another [1,2]. Due to the complexity and interconnectivity of the domain, it is very sensitive to external factors, as was demonstrated by the COVID-19 pandemic that dramatically affected the air transportation sector, which led to a significant drop on the demand side in 2020 and 2021. Starting with the post-pandemic period, the focus of the stakeholders was on cost efficiency, operational reliability and adapting to continuous passenger growth. The European Union countries recovered from the COVID-19 pandemic shock and are focusing nowadays on identifying the most feasible boarding methods that also save costs and time and how operational activities could be improved.

A balanced comparison between EU member states and Romania points out differences regarding the recovery level, passenger growth, airport concentration or traffic loss during COVID-19 pandemic. The investigation that has been done is descriptive and does not necessarily correlate with operational efficiency and growth in the number of passengers. In Romania, the passengers transported using airplanes are concentrated in a reduced number of airports, mainly due to the lack of regional connectivity, which could increase the number of routes and accessibility for passengers. This shows that the connectivity between regions is unbalanced, leading to significant differences between big cities, such as Bucharest, Cluj-Napoca, Timisoara, and Iași, and the rest of the regions which have less traffic flow [3,4]. Low-cost carriers, especially Ryanair and Wizz Air, have a strong presence in the Romanian air transportation market. High airplane utilization, together with rapid turnaround, represents the main characteristics of low-cost companies [5].

The COVID-19 pandemic had a severe impact on commercial flights, representing one of the biggest disruptions in history which led to a sudden decrease in passenger numbers and number of flights, having a significant impact on the revenues of airline companies and labor mobility, affecting, at the same time, the global economy that is strongly correlated with international connectivity [1]. Romania stands as one of the European Union (EU) countries, being considered an emerging market [6] that has a positive trend on the number of passengers. Romania stands as one of the countries with a strong recovery rate after the COVID-19 pandemic. The differences in air capacity restoration, border reopenings and tourism contributed significantly to the recovery, achieving a higher number of passengers than 2019 levels [1,2]. The air transportation systems in Romania remain concentrated mainly around Henri Coandă International Airport and a few regional airports, such as Cluj Napoca International Airport, Iasi International Airport, Timisoara National Airport [7], Brasov International Airport and Baneasa International Airport. The growth in the number of passengers could represent operational pressure, especially in the peak periods, due to the increased demand and the limited number of gates and available terminals or the capacity to process luggage: potential flight delays could appear due to the increased number of flights that should be managed at the same time, together with gate conflicts or inefficient boarding measures, which requires the latest technologies and new methods to be implemented in order to minimize costs and the ground time for aircrafts and for the maximization of boarding efficiency activities, together with operational processes. At the same time, it is worth mentioning that the annual increase in the number of passengers does not directly include boarding inefficiency or turnaround delays, and it relies on the operational efficiency of airline companies and airport operators.

The boarding process stands as a main component of the air transportation sector, having a significant impact on the turnaround process, and it could affect punctuality and gate and airport occupancy or the airplane utilization rate, leading to potential delays. At the same time, there is a clear difference between the growth in passenger numbers and the inefficiency of boarding processes, with traffic representing only an exposure metric utilized during research, pointing out operational activities that could be improved [8–11]. There is

a strong correlation between the boarding process and the turnaround time, gate occupation and costs for airline companies. Various analyses and simulation papers evaluated and compared boarding methods, but no universal operationally feasible technique has been accepted, due to the different research focuses, such as passenger compliance or luggage, airplane configuration or the quantification of boarding times [8,9]. Van Landeghem and Beuselinck [12] evaluated multiple boarding methods in order to identify and provide an operationally feasible method that reduces the boarding time and costs. The outcome demonstrated that the window middle aisle (WILMA) and outside-in boarding methods stand as two efficient boarding techniques, since both minimize seat interference, but it relies on operational activities and passenger compliance, having a potential impact on the effectiveness of these methods [11].

A reduction in boarding time does not directly minimize the operating cost or turnaround time, since boarding depends on the turnaround critical path. An operational improvement can only appear when the flight departure depends exclusively on the boarding process, which could minimize time and enable an earlier door-closing procedure [9,10,13–15].

The commencing supposition focuses on the potential costs and time saving by integrating existing boarding techniques that were successfully tested by researchers in their academic papers. The experimental results that were extracted from the academic community were validated against a specific number of eligible flights, which defines another supposition, namely that the optimization of the boarding process cannot be done for every flight.

The academic literature separates boarding techniques based on the sequence and how travelers are grouped. The main objective is to minimize passenger interference in order to avoid passengers blocking the aisle while storing luggage. The passenger-boarding procedure is not an isolated activity, representing a part of bigger components, airplane turnaround and passenger handling, which focus on luggage handling, passenger processing, airside procedures and airplane servicing. Some of the procedures could be done simultaneously, which minimizes the turnaround time, but due to the strong connection between all operational tasks, it is not mandatory to have an early departure if the boarding is done, but the rest of turnaround activities are underway. The performance of boarding techniques could be influenced by the Standard Ground Handling Agreement, also known as the SGHA; applicable service-level agreements, also known as SLAs; airplane types; load factor levels; passenger behavior; weather conditions; cabin configurations; etc. All factors that were previously described are part of the boarding procedures that should be achieved before every single flight. An investigation of all previously described techniques could lead to potential early departures and theoretically a potential gross cost savings. WILMA focuses on boarding window passengers first, followed by middle-seat and aisle-seat travelers, compared to the reverse pyramid, which focuses on the outside-in principle and back-to-front sequential distribution, defining boarding groups. The Steffen boarding technique introduced shifting row and seat sequencing in order to minimize aisle and seat interference, which is difficult to communicate and integrate. The assigned-seat method that was defined by Milne and Kelly focuses on individual sequence, which could minimize traveler interference, while the individual stochastic technique integrates uncertainty in boarding and passenger behavior [8,9,16–18].

Eurostat stands as one of the main data sources for EU member states. At the same time, due to the limitations of Eurostat, the 2025 data for Romania was extracted from the AAR website, and it is explored separately in order to also gain a national perspective on the air transportation sector. There is an approximately 2.37 million passenger difference between AAR and Eurostat data, which could have resulted from the validation method, reporting

date or different procedures utilized. Both data sources were not utilized and defined during the research as interchangeable datasets. The harmonized analysis of Romania and EU countries was done using the Eurostat database, focusing on identifying the main differences between an emerging country and the EU market, while the investigation of the Romanian market was done using AAR data. The focus of the analysis is to combine the existing literature presented by the academic literature and real data regarding air transportation in order to extract main solutions that could reduce boarding costs and time. The data that has been utilized was extracted from the Eurostat webpage for all European Union countries, while for Romania, the data was downloaded from the Romanian Airport Association. There are five main objectives that guided this research: the definition of the existing social and economic context on the air transportation sector, the extraction of real data and its mixture with the academic literature, the integration of boarding methods in order to calculate the boarding time, the classification of methods from the best to the worst using statistic metrics and the interpretation of the results, together with recommendations for implementation in airports.

Due to the complexity of the domain, defining several scientific questions that will guide the analysis is required in order to perform a comprehensive and clear investigation of the domain:

- SQ1: What was the cumulative impact caused by the COVID-19 pandemic disruption between the 2020 and 2022 period and the immediate impact compared to the results from 2019 for EU member states and Romania?
- SQ2: According to the theoretical assumptions that were defined in the research, which is the boarding technique that saves the most cost and time, and which is the most feasible method from an operational point of view?
- SQ3: How did the air transportation traffic evolve in Romania between 2008 and 2025 compared to EU countries?

The paper is divided into five sections: The first part focuses on an introduction of the air transportation sector, together with a definition of the scientific questions, followed by the methodology section, which explores the methods that have been identified in the academic literature and that were implemented in order to identify the technique that most minimizes time and costs and the air traffic evolution of EU countries. The third section explores the results of the analysis, while the fourth part focuses on the discussion of the results and the existing limitations of the research, followed by concluding remarks.

2. Methodology

In the second part of the analysis, a detailed analysis of the air transportation sector is provided, together with an explanation of the equations and mathematical approaches that have been performed. A comparative quantitative analysis using real data and the quantification of boarding-method efficiency stand as the main pillars of the analysis, having the purpose of minimizing operational inefficiency, costs and turnaround time by combining machine learning algorithms, the clustering method, real data from air transportation and main boarding techniques. The analysis provides two analytical components that are interconnected. The first one focuses on the recoverability capacities of Romania after the COVID-19 pandemic on the passenger traffic sector in comparison with EU member states, and the second part explores boarding-time improvements and cost savings according to multiple boarding techniques extracted from academic papers. The first year included in the analysis is 2008, which represents the initial year for consistent datasets published for the Romanian aviation market. This period includes a 12-year period, between 2008 and 2019, of the pre-pandemic span, which offers the possibility of defining an evolution of the number of passengers and quantifying the impact of the COVID-19 pandemic between 2020

and 2022. Therefore, the 2008 year should be considered as the starting data points instead of an economic or operational benchmark, representing, at the same time, the second year after the inclusion of Romania into the EU.

Country-level information regarding commercial flights and the passenger traffic for EU member states between 2008 and 2025 were extracted from Eurostat [19] using the "avia_paoc" dataset, while for Romania, information at the airport level was extracted from the "avia_paoa" dataset [20], while data from 2025 for Romania used the Romanian Airport Association (Asociația Aeroporturilor din România) website [7]. Regarding boarding methods, information was obtained from the academic literature, where authors such as Milne and Kelly discuss the assigned-seat, reverse pyramid, WILMA, optimized Steffen, and stochastic boarding assignment technique [8,9,16,21]. For 2025, Eurostat published data for 23 countries out of 27, lacking data for Malta, Belgium, Estonia and France.

The data coverage is different based on the purpose of the analysis. For instance, the harmonized country comparison for 2025 includes a total of 23 EU member states, since there is no available data for France, Malta, Estonia and Belgium on the Eurostat database. The second analysis includes a cumulative-impact calculation of the COVID-19 pandemic disruption for the 2020–2022 period for all EU countries, and the last evaluation is of the Romanian air transportation sector using AAR data without attaching it to the Eurostat dataset. Therefore, for the AAR Romanian transportation evaluation, EU27 and EU23 should be understood as three different descriptive analyses. The flight data that was utilized in the analysis of boarding techniques was extracted from the Eurostat dataset ("avia_paoc") using annual frequency for commercial air flights, including non-scheduled and scheduled flights. A total of 164,251 commercial flights were included for Romania in 2024 and 174,834 flights in 2025, calculated based on the passenger-growth-factor value between 2024 and 2025, since the 2025 values were not available. The dataset extraction was done on 16 June 2026.

Due to the significant impact of COVID-19 on the air transportation sector, the 2020 and 2021 years were not treated as usual data points since the passengers and airline companies had to respect lockdowns, quarantine periods, and social distancing, which in the end led to structural breaks. The boarding investigation utilizes a scenario estimation instead of quantifying realized operational potential savings. According to the existing academic literature, boarding techniques are applicable for a specific eligible flight, and it is mandatory to define them beforehand in order to quantify their impact. In order to correctly test boarding methods, there are three necessary conditions to be achieved: boarding should depend on the turnaround critical path; all boarding procedures, such as fueling, cleaning, catering and luggage loading, should be done before the finalization of boarding; and the time saved should lead to an early departure of the flight. Multiple metrics are calculated and explained in this section, such as the COVID-19 shock, the pre-COVID compound annual growth rate (CAGR) and the post-COVID CAGR.

The performance of boarding techniques mainly depended on two criteria, operational feasibility, which refers to the possibility of implementing the technique by taking into consideration passenger compliance, gate-activity requirements, sequencing difficulty or passenger communication, while the second criterion represents a theoretical optimization that quantifies the estimated cost and time savings extracted from the existing scientific literature. The boarding method that theoretically saves the largest amount of time and money is not necessarily the most feasible one from an operational point of view.

In the analysis, the potential time saved by the boarding techniques is considered as a scenario supposition, and time and cost savings could be achieved only if boarding relies on the critical turnaround path or delays, which means that all other parallel operational activities should be done on time. The analysis does not assume that the time and cost

savings obtained by implementing different boarding methods automatically minimize the operating expenses of airline companies.

2.1. COVID-19 Pandemic Impact and Passenger Traffic Evolution

This first subsection of the Methodology Section explores the equations used to calculate the evolution of air passenger traffic and quantify the impact of the COVID-19 pandemic disruption.

In order to standardize the information that was used during the analysis, the Equation (1) formula was defined. Due to the different measures that were used in the data, such as the number of passengers, which is expressed in millions, and the growth rate, which is expressed in percentages, it is impossible to combine and compare them without proper standardization.

$$z\,(standardization) = \frac{x - mean}{standard\ deviation} \tag{1}$$

Equation (1). Standardization formula.

The initial COVID-19 shock was calculated as a percentage change between the passenger traffic values between 2019 and 2020, and it is presented in Equation (2). The metric catches the immediate impact registered in 2020, and it should not be considered as a metric of the cumulative disruption of the entire pandemic span.

$$Initial\ COVID\text{-}19\ shock = \frac{Traffic_{2020} - Traffic_{2019}}{Traffic_{2019}} \times 100 \tag{2}$$

Equation (2). COVID-19 shock formula.

Due to the travel restrictions that continued in 2021 and partially in 2022, the 2019–2020 period was utilized as a descriptive evaluation of passenger evolution for 2020, 2021 and 2022 relative to 2019, which was the last year in the pre-pandemic era. It is worth mentioning that there is a clear difference between the immediate effect caused by the COVID-19 pandemic in 2020 and the rebound trajectory, and this should express the changes in 2019–2020 as a cumulative impact of the complete 2020–2022 pandemic span.

The cumulative impact cause by the COVID-19 pandemic between 2020 and 2022 is presented in Equation (3). The maximum operator that was utilized prevents the traffic values from exceeding the pre-pandemic 2019 registered values and from being considered as a loss.

$$CumulativeLoss_{2020\text{–}2022} = \sum_{t=2020}^{2022} \max(0, Traffic_{2019} - Traffic_t) \tag{3}$$

Equation (3). Cumulative impact of COVID-19 between 2020 and 2022.

The disruption caused by the COVID-19 pandemic can be easily observed by comparing the number of passengers carried in 2020 compared to 2019. In Equation (3), the impact of the COVID-19 pandemic is estimated using the traffic values from 2020 and 2019. A negative result shows a contraction compared to 2019. It does not represent a cumulative impact of the entire COVID-19 pandemic period. Due to the quarantine and operational and travel restrictions, disruptions also continued in 2021 and partially in 2022. Therefore, the number of passengers that were transported in 2020, 2021 and 2022 are explored together in the descriptive section in order to differentiate it from the initial traffic disruption.

The normalization process is one of the most important steps that should be taken prior to a comparison between numerical metrics that have different scales. Equation (4)

shows the formula for transforming the values of all 23 countries included in this research by using min–max normalization.

$$Normalization = \frac{\mathrm{x} - \mathrm{minEU23}\ (x)}{\mathrm{max}EU23\ (x) - \mathrm{minEU23}(x)} * 10 \tag{4}$$

Equation (4). Normalization formula.

The division between the latest value and the first value and then the 1/n root of the division minus one returns the compound annual growth rate, as shown in Equation (5).

$$CAGR_{post} = \left(\frac{Y_{end}}{Y_{start}}\right)^{1/n} - 1 \tag{5}$$

Equation (5). Post-COVID CAGR formula.

2.2. Cost Saving and Boarding Time Simulations

This second subsection explores the boarding time and potential cost saving equations that were utilized in various simulation processes.

The total-minutes-saved formula is presented in Equation (6). Commercial passenger flights include the total commercial flights of the country, f, based on the boarding technique, b. In this case, q stands as the percentage of eligible flights that was included in the estimation of the technique, and the outcome should be understood as a gross theoretical prediction rather than operational savings. The standard scenario utilizes the value of q = 1, which means that all flights are eligible.

$$MinutesSaved_{f,b,q} = \frac{CommercialPassengerFlights_f \times q \times \Delta t_b}{60} \tag{6}$$

Equation (6). Minutes-saved formula.

Equation (7) calculates the avoided boarding hours by converting the avoided boarding minutes by 60.

$$Avoided\ boarding\ hours = \frac{Avoided\ boarding\ minutes}{60} \tag{7}$$

Equation (7). Formula for avoided boarding hours.

2.3. Prediction and Accuracy Methods

In this third subsection of the Methodology Section, forecasting metrics are defined, which will provide a clear overview of the air transportation sector of Romania and EU member states, facilitating answering SQ1, SQ2 and SQ3. The metrics were utilized exclusively to compare the accuracy of the algorithms included in analysis.

The mean absolute error formula is explained in Equation (8), and it shows the error between the predicted values of the statistical algorithm and the real values.

$$MAE = \frac{1}{n} * \sum_{k=1}^{n} |\mathrm{yk} - \hat{y}k| \tag{8}$$

Equation (8). Mean absolute error formula.

The root-mean-squared error quantifies errors by calculating the difference between real values and predicted ones, squares the results, and divides the total number of data points, according to Equation (9). In this case, y_k represents the observed data point, while $\hat{y}_k$ is the predicted data point, and the n is the total number of observations that exist in the

analysis. The utilization of a square-root operator provides the possibility of comparing, in the same units, traffic values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_k - \hat{y}_k)^2} \tag{9}$$

Equation (9). Root-mean-squared error formula.

The formula used for the calculation of the mean absolute percentage error (MAPE) is shown in Equation (10), and it takes into consideration the difference between predicted and real values, divided by real values and calculated as a percentage.

$$MAPE = \frac{1}{n} * \sum_{k=1}^{n} \frac{|\mathrm{yk} - \hat{y}k|}{\mathrm{yk}} * 100 \tag{10}$$

Equation (10). Mean absolute percentage error formula.

A new and improved MAPE, known as a symmetric mean absolute percentage error (sMAPE), is defined in Equation (11), and it also takes into account underpredictions and overpredictions, unlike the previous method, in order to achieve a complete overview on a symmetry level.

$$sMAPE = \frac{200}{n}\sum_{k=1}^{n} \frac{2|y_k - \hat{y}_k|}{|y_k| + |\hat{y}_k|} \tag{11}$$

Equation (11). Symmetric mean absolute percentage error formula.

In order to check if the predictions are systematically above or below the real values, the bias metric calculates the level of predictions. A value close to zero represents a model that does not overpredict or underpredict the values, but at the same time, it does not point out high estimation accuracy, due to the possibility of offsetting the positive and negative values, and in order to interpret the bias value, it is necessary to include the MASE, MAPE, sMAPE, RMSE or MAE metrics. The formula for bias is presented in Equation (12).

$$Bias = 100 * \frac{\sum_{k=1}^{n}(\hat{y}k - \mathrm{yk})}{\sum_{k=1}^{n}\mathrm{yk}} \tag{12}$$

Equation (12). Bias formula.

The benchmark that has been frequently utilized to scale predicted errors for mean absolute scaled errors, also known as MASEs, is the in-sample naive scale, and the formula is presented Equation (13), where the difference between the predicted and last-year value is determined by dividing by the previous-year value (T − 1).

$$Q = \frac{1}{T-1}\sum_{t=2}^{T}|y_t - y_{t-1}| \tag{13}$$

Equation (13). In-sample naive scale formula.

According to Equation (14), the MASE formula involves the division of the MAE and the in-sample naive scale formula. The denominator that is used in the formula represents the absolute mean of the first difference for the observed data, representing the average absolute error for a one-step estimated calculation for the training dataset of the naive benchmark.

$$MASE = \frac{\frac{1}{n}\sum_{k=1}^{n}|y_k - \hat{y}_k|}{Q} \tag{14}$$

Equation (14). MASE formula.

In the above equations, yk represents the observed passenger value, while $\hat{y}k$ is the estimated value, and n is the total data points included in the analysis. MAPE and sMAPE

stand for the main metrics utilized to estimate the prediction error in percentages, while the MAE calculates the mean absolute error, and the RMSE provides a higher weight for the bigger errors. The MASE was included in this research to compare the algorithms with the naive base benchmark, while the bias shows the direction of the estimated error, but in order to be representative for the analysis, it should be interpreted alongside the rest of the metrics.

This methodological section is aligned with all three scientific questions by focusing on the COVID-19 pandemic disruption and the rebound capacity of the markets. The boarding techniques and algorithms that were included in the analysis were extracted from the academical community, together with the inclusion of potential time and cost savings, while the comparison between Romania and EU member states was done using specific and standardized annual traffic metrics.

The main indexes that are used during the analysis are described in Table 1, together with an explanation for each one.

Table 1. Metrics used in the analysis.

Metrics	Description
2015–2019 CAGR recovery	This is another growth scenario, but this time, it takes into consideration the period before COVID-19 and between 2015 and 2019 and calculates the compound yearly passenger growth rate, and it includes the rate in the latest period [2].
Post-COVID CAGR	The compound annual growth rate (CAGR) is a rebound growth scenario which takes into account the mean compound recovery rate after the COVID-19 shock, according to Equation (13) [2].
COVID-19 pandemic shock	This quantifies the traffic reduction between 2019 and 2020 due to the COVID-19 shock, according to Equation (4) [22].
Traffic recovery and growth index	This represents the average between the normalized number of passengers in 2025, the normalized growth rate between 2025 and 2024, the normalized growth rate between 2025 and 2019, the normalized international share in 2025 and the normalized domestic share in 2025.
Traffic and growth exposure index	This represents the average between the normalized number of passengers in 2025, the normalized growth rate between 2025 and 2024, the normalized growth rate between 2025 and 2019, the normalized international share in 2025 and the normalized traffic recovery and growth index.

Using composite metrics, a descriptive analysis was achieved in order to quantify the traffic growth and passenger volume evolution by including, at the same time, equal weighting since there is no research work that assigns various weights. At the same time, there is no direct connection to airplane type, boarding duration, load factor level, gate congestion or luggage interference, and traffic exposure should not be considered as a metric of boarding inefficiency and delays.

The accuracy metrics that quantify the effectiveness of the ML algorithm are presented in Table 2, together with examples from the academic literature.

The ML techniques that were utilized during the analysis are presented in Table 3 in order to understand how to integrate them according to academic literature research.

Each algorithm that was included in the analysis was trained based on the information extracted from Eurostat and the AAR. The datasets contain limited data points and the COVID-19 pandemic disruption period, which makes it difficult to classify the accuracy of the ML algorithms tested. The accuracy of the models was tested using the rolling-origin back testing technique in order to not alter the chronological period and to prevent including

bias from future information that could have been used in the historical estimations. Using this procedure, the whole process becomes more transparent and easier to follow but is still limited by the small data samples available. The algorithms that were integrated were tested and compared based on the same scenarios and the same evaluation framework.

Table 2. Description of accuracy metrics.

Metrics	Description
MAE	The mean absolute error (MAE) calculates the absolute difference between the estimated values and the real ones as a mean, according to Equation (5) [23].
RMSE	The root-mean-squared error (RMSE) quantifies the square root for the mean squared estimated errors using the formula presented in Equation (6) [23].
MAPE	The mean absolute percentage error (MAPE) estimates the mean error predicted compared with real values as a percentage using the Equation (7) formula [24].
sMAPE	The symmetric mean absolute percentage error (sMAPE) stands as a new error method that takes into consideration underpredictions and overpredictions in order to achieve higher symmetry, calculating the results as a percentage according to the formula from Equation (8) [24].
MASE	The mean absolute scaled error (MASE) explains the prediction error by comparing the results between various metrics, such as countries in our case. MASE stands as a non-negative metric used to quantify the error measure. A value of one means that there is equal performance between the evaluated algorithm and the naive benchmark, while if the value is smaller than one, this shows better performance for the investigated algorithm than the naive benchmark. If the value is higher than one, then the naive benchmark outperforms the investigated model. Equation (12) includes a division between the MAE and in-sample scale formula (Q) from Equation (11) [24].
Bias	This quantifies the forecast direction instead of the overall accuracy of the model, and if the result of Equation (10) is positive, this means that the model is over forecasting, otherwise, it is under forecasting for negative values, or there is no strong mean direction if the bias is close to zero [25].

Table 3. Description of machine learning techniques.

Metrics	Description
Standardization	This represents a transformation method that converts values in order to have a standard deviation value of 1 and a mean of 0, and it is mandatory when a clustering is done due to different scales and units. In our case, the number of passengers is expressed in millions, while growth is expressed in percentages [26].
Kmeans Clustering	This is an unsupervised technique that groups data into a specific number of groups, also known as clusters, focusing on minimizing the sum of squared distances in clusters. This represents an unsupervised algorithm search for hidden patterns into data without having the possibility to learn from labeled data [27,28].
PCA	Principal component analysis, also known as PCA, represents a dimensionality reduction algorithm that converts features that are correlated into a smaller number of new variables, which are called principal components, containing similar variance and information as the initial dataset [29].
Exponential Smoothing	Holt additive trend exponential smoothing is an estimating model used in time series analysis which focuses on trends, but not on seasonality, providing a higher weight for recent data and smaller weight for older data [30].
SVR	Support vector regressor (SVR) stands as one of the most utilized ML techniques, being designed to estimate continuous values, having good efficiency for stock price predictions or time series forecasting, defining a balance between the fitted data points and the possibility of overfitting, and having the capability to identify non-linear correlations between features [31].

Table 3. *Cont.*

Metrics	Description
Lasso Regression	This is a linear prediction algorithm that can automatically select features. Lasso represents an acronym of Least Absolute Shrinkage and Selection Operator, and it predicts a linear relationship among independent features and the target variable, and it penalizes the coefficients that have high values or if the utility of coefficients is limited [32].
Drift	This is a time series predictive model which considers that features will change by the mean historical absolute value for every single period [33].
2015–2019 CAGR Recovery	This is another growth scenario, but this time, it takes into consideration the period before COVID-19, between 2015 and 2019, and calculates the compound yearly passenger growth rate, and it includes the rate in the latest period [2].
Post-COVID CAGR	The compound annual growth rate (CAGR) is a rebound growth scenario which takes into account the mean compound recovery rate after the COVID-19 shock, according to Equation (13) [2].
Naive Baseline	This is one of the simplest prediction methods, and it assumes that the latest data point is the best in predicting the future value [24].
Damped Drift	This is a very effective benchmark model for time series analysis and predictions, including innovative methods. The algorithm takes into consideration mathematical approaches such as Riccati equation in order to estimate the error state of vectors and the covariance matrix [34].
Extra Trees	Also known as Extremely Randomized Trees, these represent an extension of the random forest algorithm, but the logic includes randomness, focusing on finding relevant results based on chaos. Extra trees is an ensemble ML algorithm which takes into consideration multiple decision trees, and it splits randomly instead of searching for optimal thresholds [35].
Log Extra Trees	These are an extension of the extra trees algorithm, including also the logarithmic transformation of target features since there can be significant differences in passenger volumes between countries [36].

The five boarding methods that are used during this research are described in Table 4: optimized Steffen, assigned seat, individual stochastic boarding assignment, reverse pyramid and window middle aisle (WILMA).

A comparison of all five boarding techniques that were included in the analysis is shown in Table 5, presenting, at the same time, the study purpose, airplane and sample data, luggage suppositions and compliance, the reference technique to compare, the potential time saved and transferability limitations.

The potential time and cost savings were extracted from academic papers which utilized various passenger groups, luggage suppositions, boarding techniques, airplane configurations or experimental conditions; therefore, the savings are not necessarily comparable and are treated as individual experimental scenarios, assuming transferability to all EU markets, including to Romania. In order to integrate the results, validation using real flight-level data should be achieved.

At the same time, the methodology included an analytical part, where the airports and countries that have a higher number of commercial flights have a bigger chance of adapting new boarding methods and benefiting from potential time and cost savings, while the countries that had a post-pandemic strong rebound need more careful analysis due to the possibility of gate delays or delays related to cabin luggage, together with an increased boarding time.

Table 4. Description of boarding methods.

Metrics	Description
Optimized Steffen	The focus of this technique is to minimize seat and aisle interference by boarding passengers in rotation based on seat position and rows, focusing especially on window seats, which do not block the rest of the boarding procedure [21].
Assigned seat	This method assigns passengers to a boarding group or a seat in a manner that tries to minimize the interference between passengers, and it is considered by the authors to be the optimized Steffen method [16].
Individual stochastic boarding assignment	This is a passenger-assignment simulated technique that predicts passenger movement by taking into consideration potential uncertainty and interference, being unique compared with the rest of the models that focus on assigning passengers to a specific boarding group [8].
Reverse pyramid	This is a boarding method that combines the back-to-front and WILMA techniques, grouping the passengers in the back and first boarding the passengers in window seats, then the passengers that are in the front and aisle seats [37].
WILMA	According to this technique, passengers that have seats at windows are boarded first, followed by middle-seat passengers, while the passengers with aisle seats are boarded last. This method tries to minimize interference between passengers in order to avoid the time spent standing up and to allow people to reach their seats [17].

Table 5. Boarding techniques' potential time savings, scope of the analysis and transferability limitations.

Metrics	Study Purpose	Airplane and Sample Data	Luggage Suppositions and Compliance	Potential Time Saved	Reference Technique	Transferability Limitations
Optimized Steffen	Full-scale experiment	Replica of Boeing 757; six seats per row, with 12 economy rows, 72 passengers, and a single aisle	Passengers used a troller, bag or both, based on the prescribed conditions and respected the seat allocation	A total of 155 s saved per flight, representing a saving of approximately 41.78%	Back-to-front technique with a total boarding time of 371 s	Difficult to communicate with passengers in the individual sequence and to keep the whole boarding process under control
Assigned seat	Simulation and optimization	A fully loaded simulated airplane	Seat allocation which takes into account the passengers' luggage, but it is mandatory to obtain information prior to boarding	A total of 164.6 s saved per flight, representing a saving of approximately 44.37%	Alternative boarding techniques, using 371 s as a benchmark for boarding duration	The simulated results should not be considered as realized savings, since the scenarios tested were done based on specific assumptions
Individual stochastic boarding assignment	Stochastic experiment	Simulated boarding; no experimental sample available	Uncertainty, interference and travelers' movement were considered stochastically	A total of 92.75 s saved per flight, representing a saving of approximately 25%	Traditional boarding methods	Founded on a scenario supposition instead of using observed data to minimize the boarding time
Reverse pyramid	Simulation and air transportation integration of analytical techniques	America West Airlines flights	Passengers were grouped, combining outside-in and back-to-front methods	A total of 74.2 s saved per flight, representing a saving of approximately 20%	Traditional boarding methods	The outcome is not transferable for all operational activities since the outcome comes from a specific airline implementation
WILMA	Full-scale experiment	Replica of Boeing 757; six seats per row, with 12 economy rows, 72 passengers, and a single aisle	Passengers used a troller, bag or both, based on the prescribed conditions	A total of 118 s saved per flight, representing a saving of approximately 31.81%	Back-to-front technique with a total boarding time of 371 s	The performance relies on the airplane type, luggage distribution, number of groups and passengers' compliance

In order to improve the accuracy and robustness of the forecasting methods, a rolling back testing technique was integrated instead of using a single fixed period, and in this case, the training dataset was extended sequentially over time, which led to a one-year-ahead prediction for each algorithm tested. The first prediction was done for 2017 based on information available until 2016. For the prediction in 2018, the data until 2017 was used, and the rest of the period was determined recursively until the whole dataset was utilized, which makes the testing of the algorithm more robust and relevant for comparison. The rollback integration for air passenger evolution is relevant since it takes into consideration the historical time series available, and it excludes any future information when the past values were predicted. For every single predicted value, a comparison with the real value was performed in order to quantify the accuracy of the model by calculating the RMSE, MAE, MAPE, Bias, MASE and sMAPE. The classification of the algorithms was performed based on an average rank, with lower results meaning better performance, across all six features included in the analysis. Due to the severe impact of the COVID-19 pandemic on the air transportation sector, the back testing technique returns estimations per year by comparing the period before, during and after the COVID-19 pandemic, pointing out the capacity of countries to recover after the significant disruption that occurred. An estimation of the results per year avoids hidden effects of the COVID-19 pandemic compared to an aggregated metric, allowing for, at the same time, an understanding of how the crisis impacted the domain [25,38].

3. Results

The boarding process outcomes should be interpreted as estimations of various scenarios tested on experimental and simulation systems. According to the scientific literature, time reduction does not automatically impact every commercial flight, and it relies on the load factor of the aircraft, gate occupancy, the luggage volume, and the airplane type of passenger compliance. Initially, a descriptive analysis was performed in order to better understand the dataset. The efficiency of the boarding methods was determined based on operational assumptions, and the potential savings should be interpreted as scenario estimations according to existing literature analyses and should take into consideration the commercial level of each country. The initial assumption is that the estimated potential time saved in the academic literature is transferable to all flights investigated. The second assumption refers to the level of compliance during boarding instructions, which is high enough to be applied in reality, while the last assumption shows that the boarding techniques are applicable for all available cabins, airplanes, gate configurations and operational activities. At the same time, the investigation takes into consideration that the boarding process is close to the critical level of the turnaround, and a minimization in the boarding time means a possible turnaround saving only if boarding is on the critical path. The results demonstrate the maximum operational exposure instead of turnaround minimization.

The monetary expression that was used during the analysis is in USD, or the United States Dollar. There are multiple scenarios regarding the potential saving per minute. According to the academic literature, USD 30 per minute represents the conservative scenario, while USD 75 per minute stands as an intermediate scenario, and USD 150 per minute is the optimistic scenario. In order to make sure this investigation was as close to reality as possible, the USD 30 value was considered as a conservative option. All three scenarios represent different sensitivity assumptions instead of universal applicable delay expenses. The investigation integrates the USD 30 per minute scenario, while the outcome includes theoretical exposure, excluding staff training and passenger communication of implementation costs and calculating the gross expenses.

The difference between the values expressed by Eurostat and the AAR for Romania is approximately 2,372,305 passengers, and it represents the number of passengers transported in December 2025, which was not yet published by Eurostat, but in order to make a relevant comparison with the rest of the EU countries, the values from Eurostat were kept and used in the graphical representations and analysis.

3.1. Romania Analysis

A description of the Romanian air transportation domain is provided in Table 6. The extracted dataset contains information regarding the number of passengers between 2008 and 2025. In the first year investigated, a total of 8,416,394 passengers were transported in Romania, compared to 28,547,056 in 2025, which represents a growth of 239.18%. The largest three airports in Romania reflect around 80% of the national passenger traffic in 2025. The Henri Coanda International Airport, also known as OTP, is the biggest and busiest airport in Romania, having a share of 59.56% in 2025 among all 17 Romanian airports. The top three airports in Romania represent approximately 80% (79.97%) of total passengers transported. The HHI for Romania in 2025 is 0.3821, while the CAGR is 7.45%.

Table 6. Romanian dataset description.

Metrics	Values
No. of passengers in 2008	8,416,394
No. of passengers in 2025	28,547,056
Total growth in 2008–2025	239.18%
Top 3 airport shares in 2025	79.97%
HHI in 2025	0.3821
OTP share in 2025	59.56%
Total airports in Romania	17
CAGR	7.45%

The results of the analysis of the annual number of passengers for the Romanian market is shown in Figure 1.

There is a positive trend from 2008 until 2019, starting with 8,416,394 passengers in 2008 and achieving a total of 22,807,494 passengers in 2019. Due to the COVID-19 pandemic that affected the entire air transportation industry, the number of passengers decreased drastically in 2020, achieving a minimum value of 7,042,314 passengers. Starting with 2021, the trend became positive again, with 10,977,252 passengers in 2021, followed by a significant increase in 2022 to 20,400,036 passengers when the COVID-19 pandemic restrictions were dropped, while in 2023, there was a total of 23,761,044 passengers, and in 2024, was a total of 25,427,943 passengers. The peak for Romania, according to the AAR dataset, was obtained in 2025, with a total of 28,547,056 passengers. Romania is an example of rebound after the COVID-19 pandemic, achieving and even surpassing the 2019 number of passengers in 2023, 2024 and 2025.

The evolution of the number of passengers in absolute values is described in Figure 2 for four Romanian airports: the Henri Coanda International Airport (OTP), the Avram Iancu International Airport (CLJ), the Timisoara Traian Vuia Airport (TSR) and the Aurel Vlaicu International Airport (BBU). Due to the fact that the BBU airport was closed between 2012 and 2022, the number of passengers decreased significantly because starting with 2022, only a few low-cost companies had flights due to the limited capacity of the airport. Between 2008 and 2025, over 1,029,645 passengers were lost at the BBU airport. The biggest

airport in Romania, OTP, showed an increase of almost 12 million passengers (11,937,595) between 2008 and 2025, representing the highest increase in Romania, followed by the CLJ airport, with an increase of almost 3 million passengers (2,863,580), and the TSR airport, with an increase of 548,604 passengers. In general, the trend for Romanian airports is positive, especially for the airports in big urban areas.

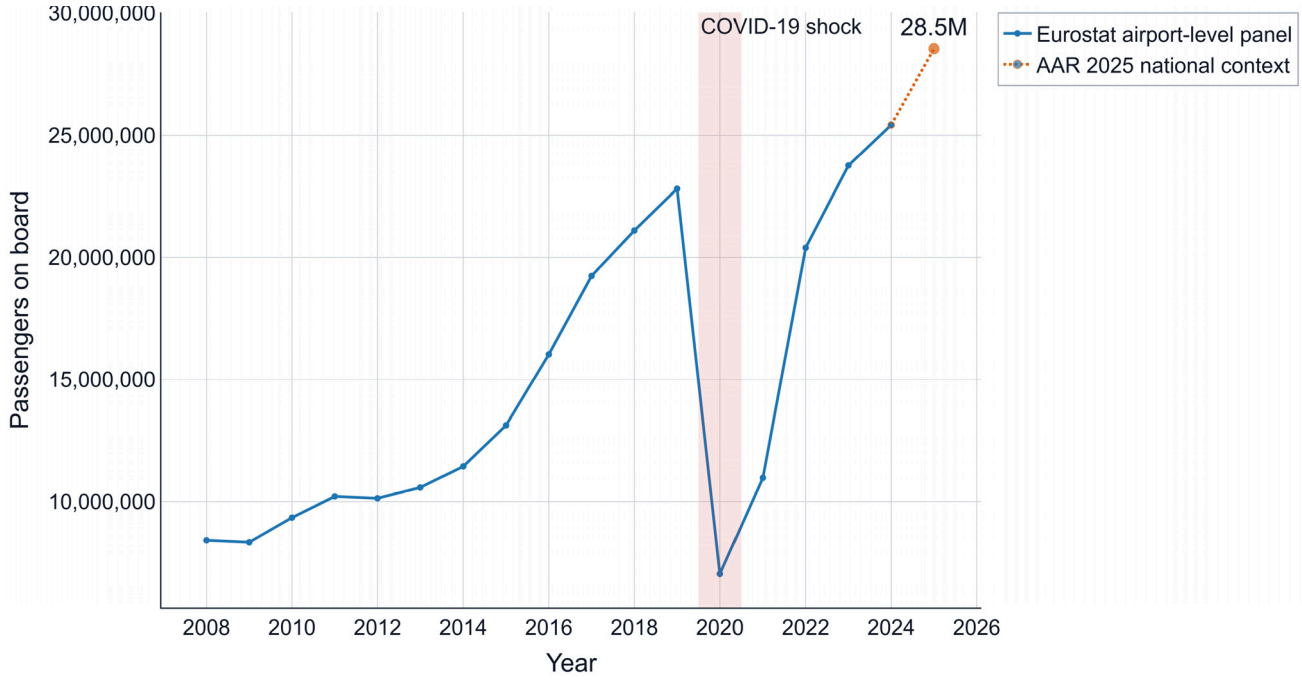

Figure 1. Yearly airport passengers' trend in Romania.

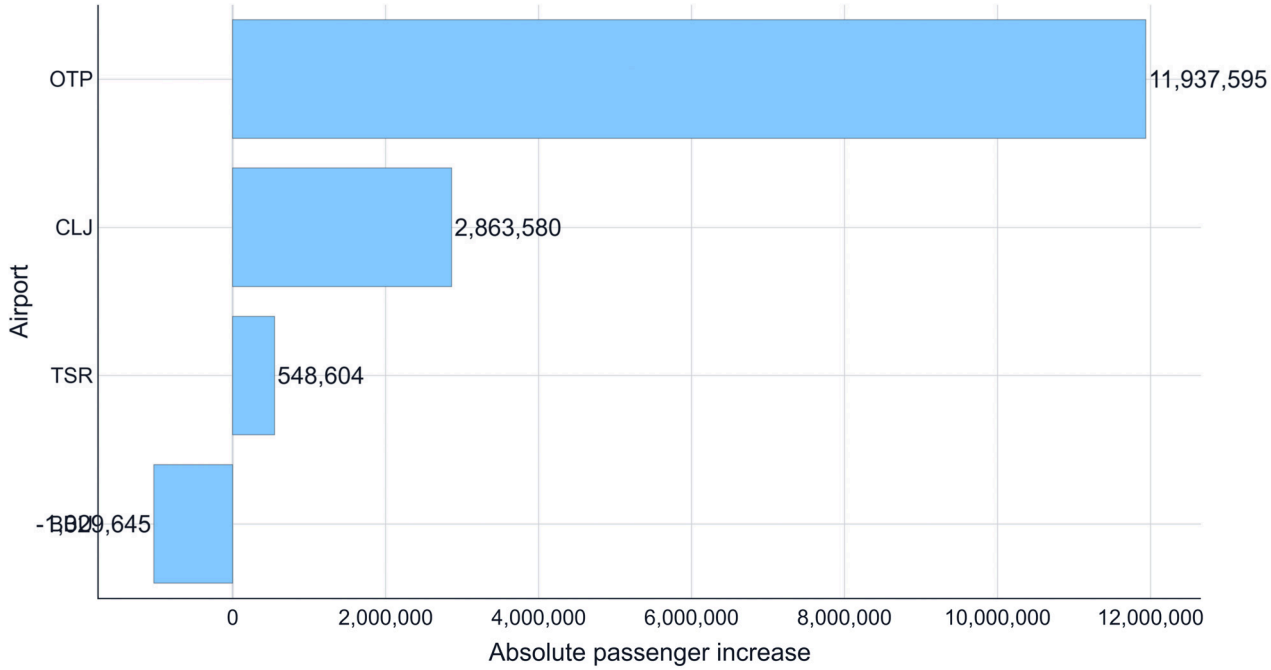

Figure 2. Romanian airports' passenger increase between 2008 and 2025. Note: The 2025 values were extracted from the AAR database, and they are presented as the national context.

The number of passengers in 2025 for Romanian airports is presented in Figure 3. The OTP airport is in first place, and it has the highest number of passengers, with a total that exceeded 17 million passengers (17,001,578), which represents a record in Romania,

followed by the CLJ airport with 3,582,134 passengers, the Iasi International Airport with 2,244,156 passengers, and TSR with 1,458,098 passengers, while the rest of airports have less than a million passengers per year.

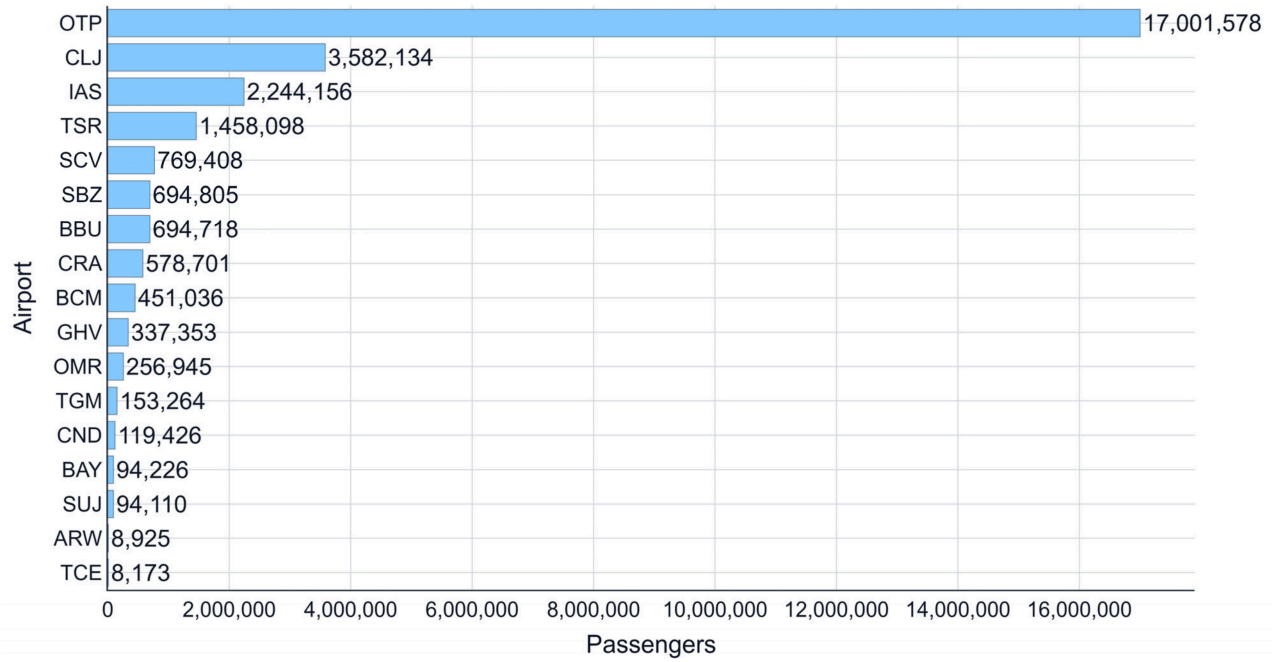

Figure 3. Romanian airports' number of passengers in 2025. Note: The 2025 values were extracted from the AAR database, and they are presented as the national context.

The yearly growth rate for the Romanian air transportation sector is pointed out in Figure 4 using two datasets, one from Eurostat, which contains information between 2008 and 2024, and for 2025 data, the AAR national website was used to extract the data.

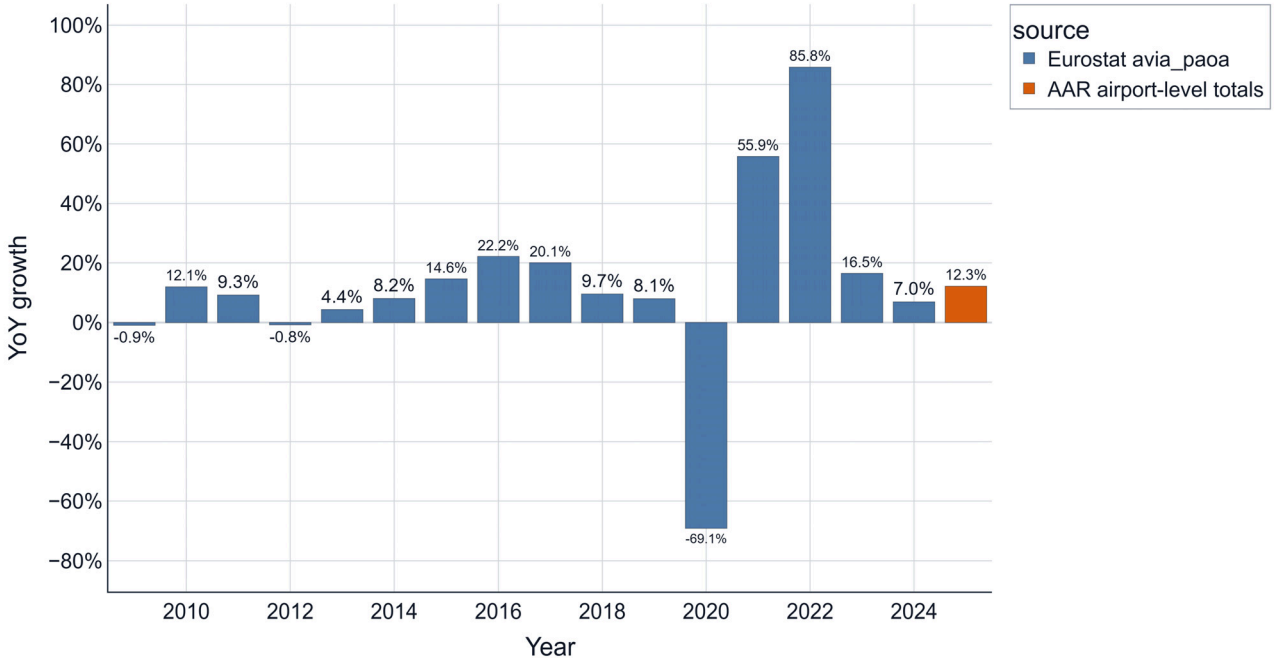

Figure 4. Year-over-year growth in number of passengers in Romania. Note: The 2025 values were extracted from the AAR database, and they are presented as the national context.

In 2009, compared to 2008, there was a small decrease of −0.9%, followed by two strong increases in 2010 of 12.1% and in 2011 of 9.3%, followed again by a small decrease in 2012 of −0.8%. From 2013 to 2019, there was a positive trend, achieving an increase of 22.2% in 2016. In 2020, due to the COVID-19 pandemic, a shock in the market occurred, leading to a decrease of −69.1% compared to 2019, because of social distancing and mobility restrictions. The −69.1% decrease should be interpreted as the immediate decrease registered in Romania between 2019 and 2020 due to the COVID-19 pandemic. It should be clearly differentiated from the 2020–2022 pandemic period. The air traffic in Romania rebounded in 2022, recovering the gap lost compared to 2019, due to the removal of restrictions. In 2021, the number of passengers increased by 55.9% compared to 2020, while the peak was in 2022, with an increase of 85.8% compared to 2021. In 2025, when the passenger record in Romania was registered, there was an increase of 12.3% compared to 2024.

3.2. EU–Romania Comparison

A comparison between the EU median, the EU top quartile and Romania is shown in Figure 5 using a radar graph type. Romania has a higher recoverability value than most of the EU countries, being above the EU median and top quartile, but lacks recent acceleration or international exposure, while the COVID-19 disruption was not so severe compared with other EU markets.

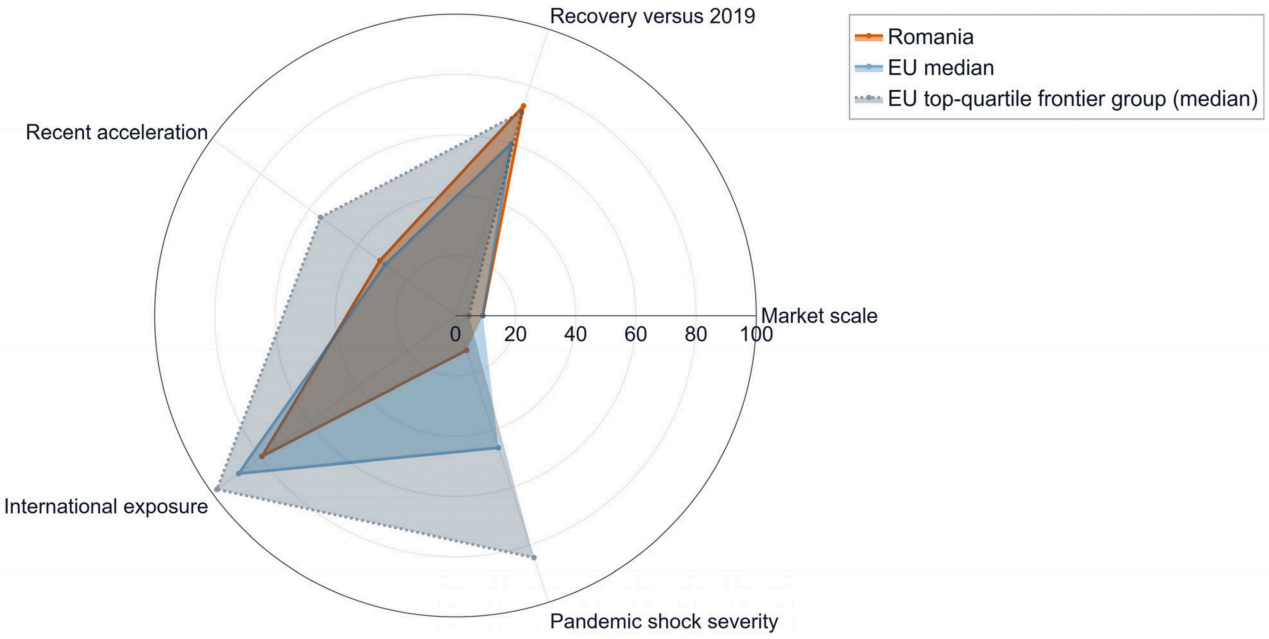

Figure 5. Romania vs. EU median and top quartile on traffic exposure profile. Note: The 2025 values were extracted from the AAR database, and they are presented as the national context.

Six different metrics were analyzed: the rebound rate compared to 2019, boarding exposure, international exposure, domestic exposure, the market scale and recent acceleration. The EU top quartile and Romania have the same rebound rate, 73.2%, compared to the EU median, which is only 60.0%, while boarding exposure is bigger for the EU top quartile (64.7%) compared to Romania (53.8%) and to the EU median (49.1%). At the same time, the international exposure for the EU top quartile (99.6%) is higher than for Romania (79.6%) and the EU median (89.1%). The domestic exposure for in the EU top quartile (0.04%) is smaller compared to Romania (20.4%) and the EU median (10.9%), while at the market scale, the EU top quartile value is 23.7%, and in Romania, and the EU median has the same value of 9.1%. For the last metric, recent acceleration, the EU top quartile has the highest

value, 43.1%, while for Romania, the value is 31.1%, and for the EU median, the value is 28.8%.

The main information regarding the 23 EU countries that were included in the analysis is presented in Table 7. The data coverage split the analysis. Due to the existing limitations of the Eurostat database, there are no available data values for France, Estonia, Belgium and Malta for 2025, so all four countries were excluded from the 2025 comparative analysis, including only 23 countries. For the 2019–2022 cumulative impact of the COVID-19 disruption, all 27 EU member states were included. In 2008, the EU countries included in the analysis had a total of 743,219,429 passengers, while in 2025, the value was 1,248,967,936 passengers. Spain is the country with the largest market in EU, representing approximately 21.79% of the total EU passengers transported. The first three countries, Spain, Germany and Italy, represent approximately 54% of the total EU market (53.86%). The total growth between 2008 and 2025 for all 23 countries is 68.05%, while the HHI value in 2025 is 0.1169, and the CAGR is 3.10%.

Table 7. European Union dataset description.

Metrics	Values
EU23 passengers in 2008	743,219,429
EU23 passengers in 2025	1,248,967,936
Largest EU market in 2025	Spain
Total growth in 2008–2025	68.05%
CAGR	3.10%
Countries included	23/27
HHI in 2025	0.1169
Spain share in 2025	21.79%
Share of top 3 countries in 2025	53.86%

Regarding the EU traffic exposure index, Romania is in 12th place among the 27 EU countries, according to Figure 6, which shows a comparison between traffic and the growth exposure index score and the boarding cost exposure index.

The countries that are on the right side have significant composite pressure, while the countries that are at the top of the graph have a high boarding cost exposure, and the bubble size reflects the number of passengers. In the top quartile, there are countries which have shown significant growth in the last few years, and which were able to rebound after the COVID-19 pandemic, such as Spain, Poland, Malta, Hungary, Croatia, the Czech Republic and Italy. Romania, together with Greece, Germany and Luxembourg, is above the EU median, while the rest of the countries are below the EU median. Romania has a traffic and growth exposure index score of 53.0, while the boarding cost exposure index is 56.65, having a growth of 14.0% between 2019 and 2024, being the 12th country based on the number of passengers from the EU.

The number of passengers carried per country in 2024 is described in Figure 7. In first place is Spain with 259,739,884 passengers, followed by Germany with a total of 199,555,603 passengers, while Italy is third with 182,370,612 passengers. As was already presented above, Romania is in 12th place in the EU, with approximately 26,174,751 passengers, being above Finland (18,695,293 passengers), Hungary (19,755,328 passengers), the Czech Republic (19,174,047 passengers), Croatia (13,459,551 passengers) and Cyprus (13,729,951 passengers).

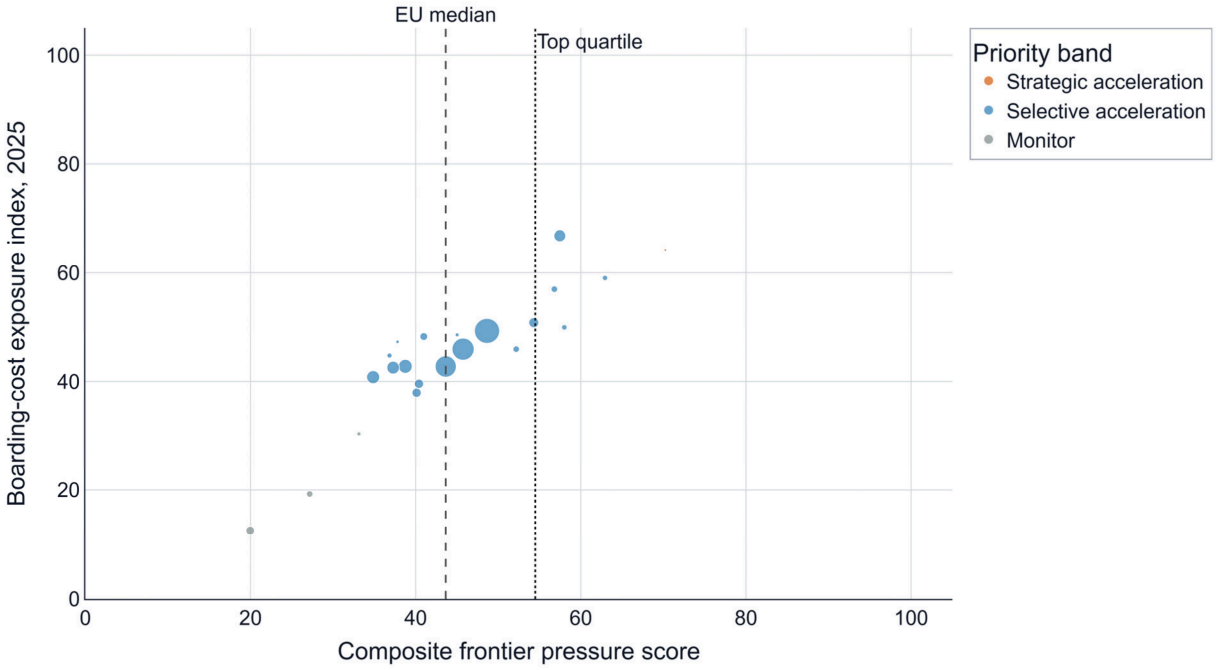

Figure 6. Traffic exposure map based on operational demand and boarding cost exposure metrics.

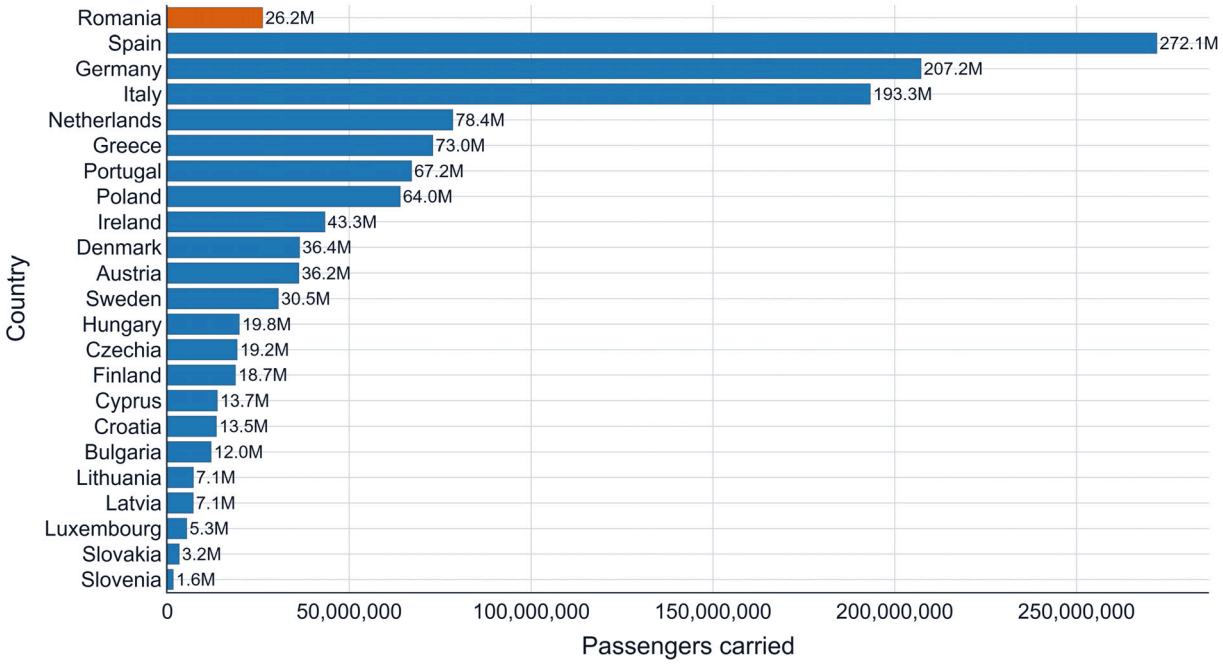

Figure 7. Air passenger traffic per country in 2025.

The disruption caused by the COVID-19 pandemic for the 2020–2022 period is presented in Figure 8. The highest cumulative loss that was recorded for EU markets was registered in Germany, with a total loss of 393.6 million passengers, representing approximately 57.9% of three times the 2019 annual values that were considered as the baseline, followed by Spain, France and Italy. Romania had a cumulative loss of around 28.14 million passengers, which represents 43.5% of three times the 2019-period values. The metric captures the pandemic disruption level for each EU market, lacking information regarding labor mobility, tourism, quarantine and testing restrictions, and airline route development.

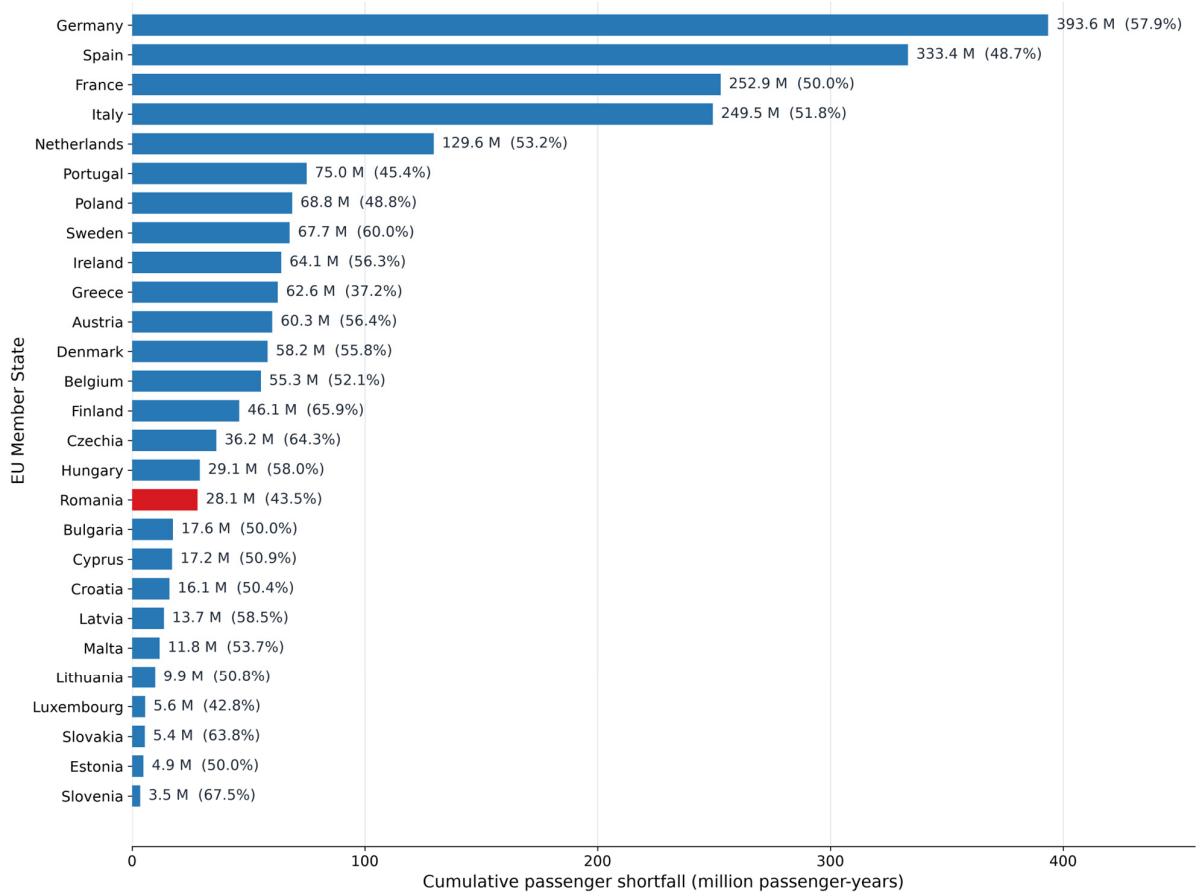

Figure 8. The cumulative impact of COVID-19 pandemic for the period between 2020 and 2022 for EU countries.

The recoverability of each European country after the COVID-19 pandemic is analyzed in Figure 9 by comparing the growth rate between 2025 and 2019 and the number of passengers carried in 2025.

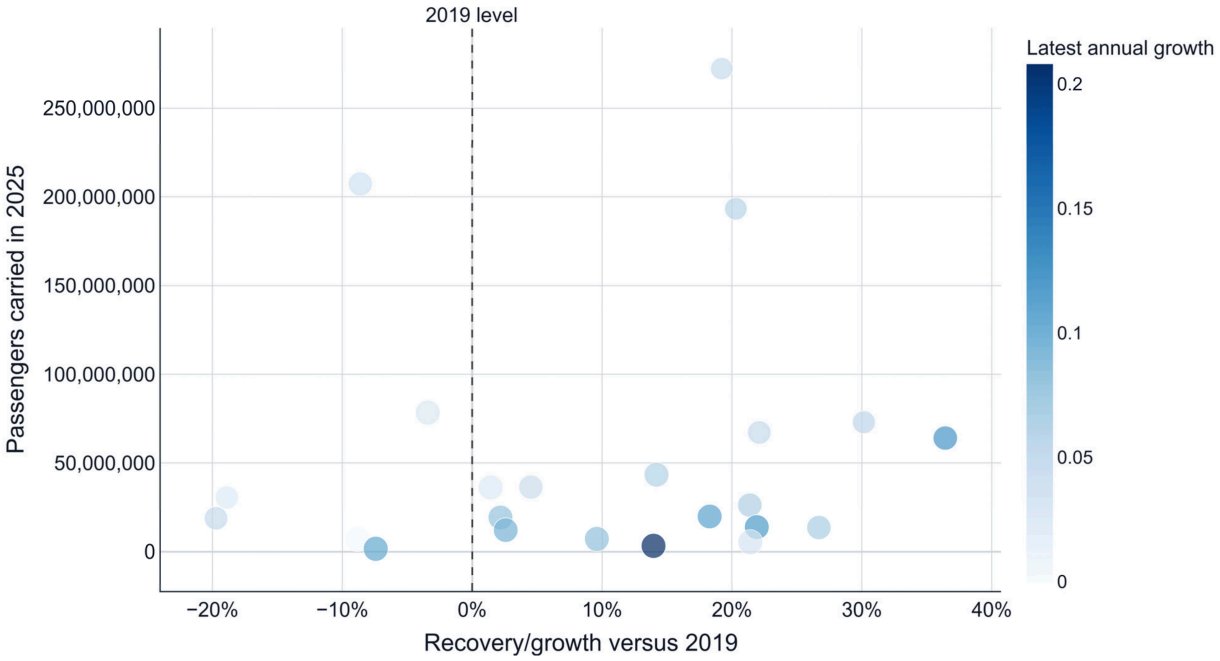

Figure 9. Rebound comparison between 2019 and 2025 for EU countries.

The country with the highest growth is Poland, which showed an increase of 36.4% from 2019 to 2025, achieving a total of 63,039,983 passengers in 2025, of which 97.2% of the passenger traffic was international, and only 2.8% was domestic, followed by Greece, which had an increase of 30.2%, achieving a total of 73,000,224 passengers in 2025, of which 85.3% of the passenger traffic was international, and 14.7% was domestic. In third place is Croatia, followed by Portugal, Cyprus and Romania, which has a growth rate of 21.4%, achieving a total of 26,174,751 passengers in 2025, and 96.2% of the passenger traffic was international, and only 3.8% was domestic. At the same time, there are countries that have still not recovered after the COVID-19 pandemic and are below the numbers from 2019, such as the Netherlands, Slovenia, Germany, Latvia, Sweden and Finland.

The volume of passenger revenue between 2019 and 2025 is compared for all 23 EU countries included in the analysis in Figure 10. The colors of the countries, as shown in the legend, point out the growth rate value. If the color is red or orange, the growth rate is close to zero or negative, and if it is green or dark green, it is a significant increase.

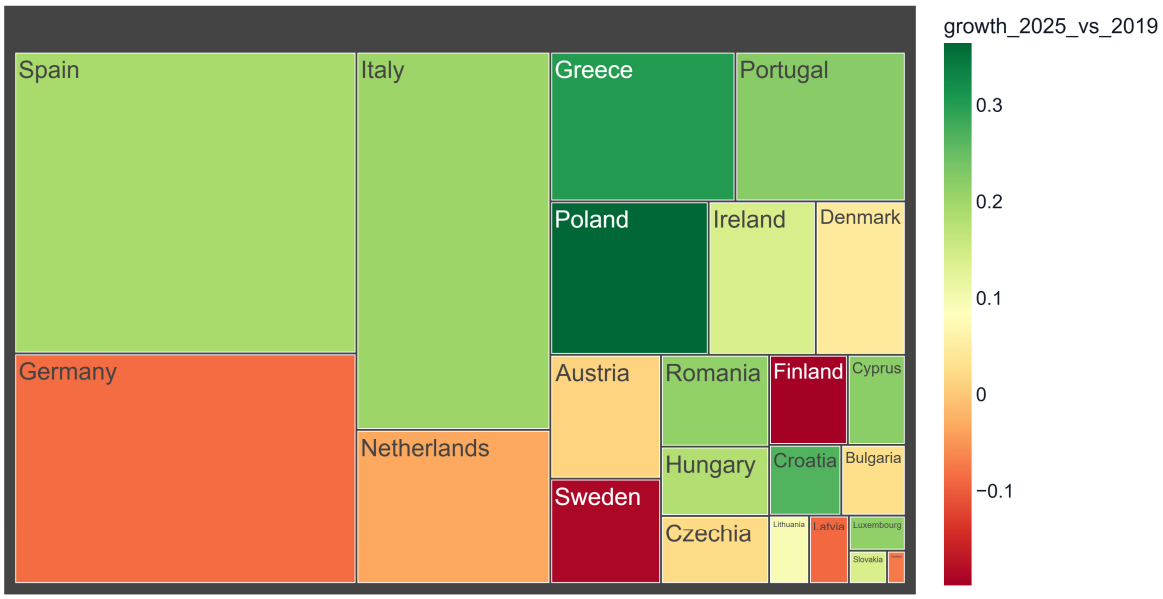

Figure 10. EU passenger volume and rebound rate between 2019 and 2025.

In first place is Spain, which had a growth of 19.21% between 2019 and 2025, representing the country with the highest number of passengers, followed by Germany, which had a limited increase, being below the 2019 passenger traffic at 8.61%, while Italy had an increase close to Spain of 20.29%. Poland is the country with the highest growth rate between 2025 and 2019, with a 36.42% increase, while Greece increased by 30.15%, Croatia had a growth rate of 26.69%, and Romania had a growth rate of 21.37%. At the same time, there are two countries which had negative growth rates: Sweden, with a growth rate of −18.88%, and Finland, which had a growth rate of −19.72%.

The ten most relevant countries from the EU and Romania are pointed out in Figure 11, which shows the annual passenger evolution between 2008 and 2025.

The country with the highest growth is Poland, which had an increase of 36.4% from 2019 to 2025, achieving a total of 63,039,983 passengers in 2025, of which 97.2% of the total flights were international, and only 2.8% of the flights were domestic, followed by Greece, which had an increase of 30.2%, achieving a total of 73,000,224 passengers in 2025, of which 85.3% of the flights were international, and 14.7% of the flights were domestic. In third place is Croatia, followed by Portugal, Cyprus and Romania, which has a growth rate of 21.4%, achieving a total of 26,174,751 passengers in 2025, and 96.2% of the total

flights were international, and only 3.8% of the flights were domestic. At the same time, there are countries that have still not recovered after the COVID-19 pandemic and are below the numbers from 2019, such as the Netherlands, Slovenia, Germany, Latvia, Sweden and Finland.

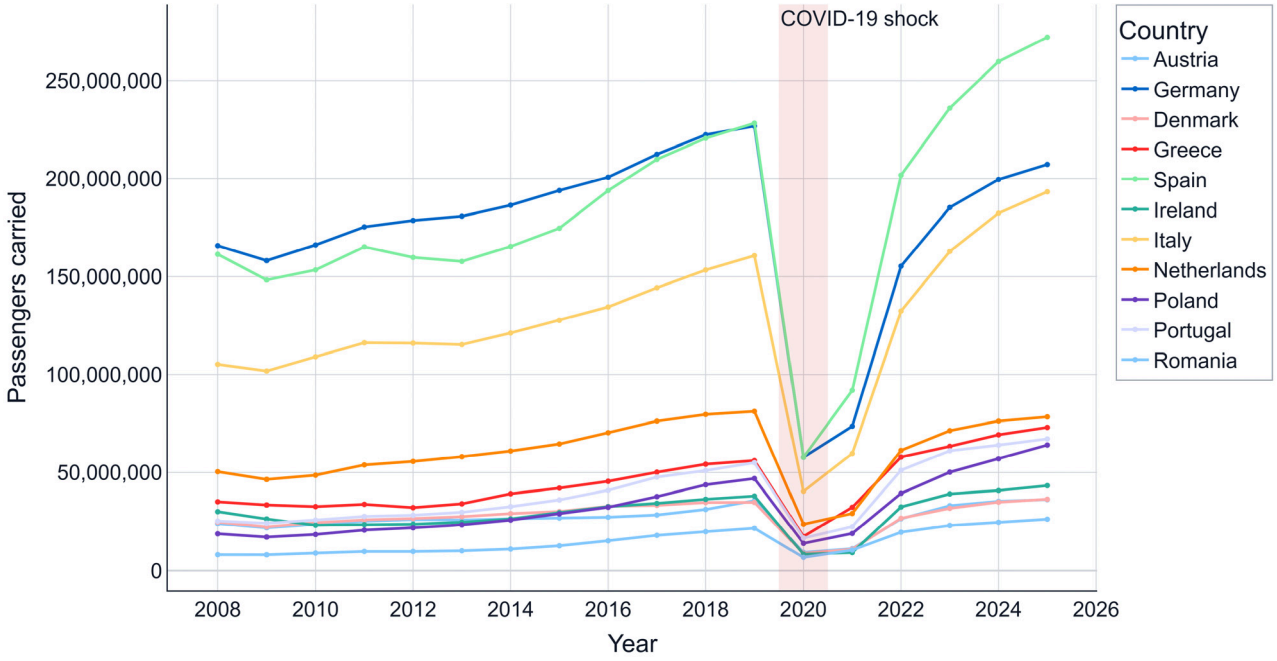

Figure 11. Yearly passenger evolution between top 10 EU countries and Romania.

The distribution of international and domestic flights in 2025 is explained in Figure 12, together with the growth rate compared to 2024. The dotted lines represent the median for international and domestic flight shares, which points out that approximately 98% of the passenger traffic was international, and only 2% was domestic. The countries with the highest percentage of international passenger traffic are the Netherlands (2.8% growth rate compared to 2024), Hungary (11.1% growth rate compared to 2024), the Czech Republic (8.0% growth rate compared to 2024), Ireland (6.1% growth rate compared to 2024), Slovenia (10.7% growth rate compared to 2024), Lithuania (8.3% growth rate compared to 2024), Latvia (no growth rate compared to 2024) and Cyprus (11.9% growth rate compared to 2024), with 100% of the flights being international due to the small size of the countries, which makes domestic flights unreliable.

A comparison between the traffic exposure index and the 2025 passenger volume is shown in Figure 13.

The index has values between 0 and 100, and it describes the rebound characteristics and the recent growth, lacking information on the level of gate congestion, boarding pressure and delays. The higher value of EU member states means that traffic exposure is higher based on the included features. The country with the highest boarding pressure is Slovakia, which is surprisingly due to the limited number of passengers, only 3,236,570 in 2025. At the same time, Slovakia had a significant increase between 2024 and 2025 of 20.8%. On the other hand, Sweden is the country with the lowest EU traffic exposure index, having a value of 19.96 and a total of 30,510,455 passengers in 2025. The EU median pressure score is 43.6, and below this value are Romania, which has a pressure score of 40.98, followed by Denmark, Luxembourg, Portugal, the Netherlands, Greece, Austria, Bulgaria, Finland, and Latvia. Italy is exactly at the EU median score with a value of 43.6, while the rest of the countries are above, and those member states require improvements in operational activities and boarding processes.

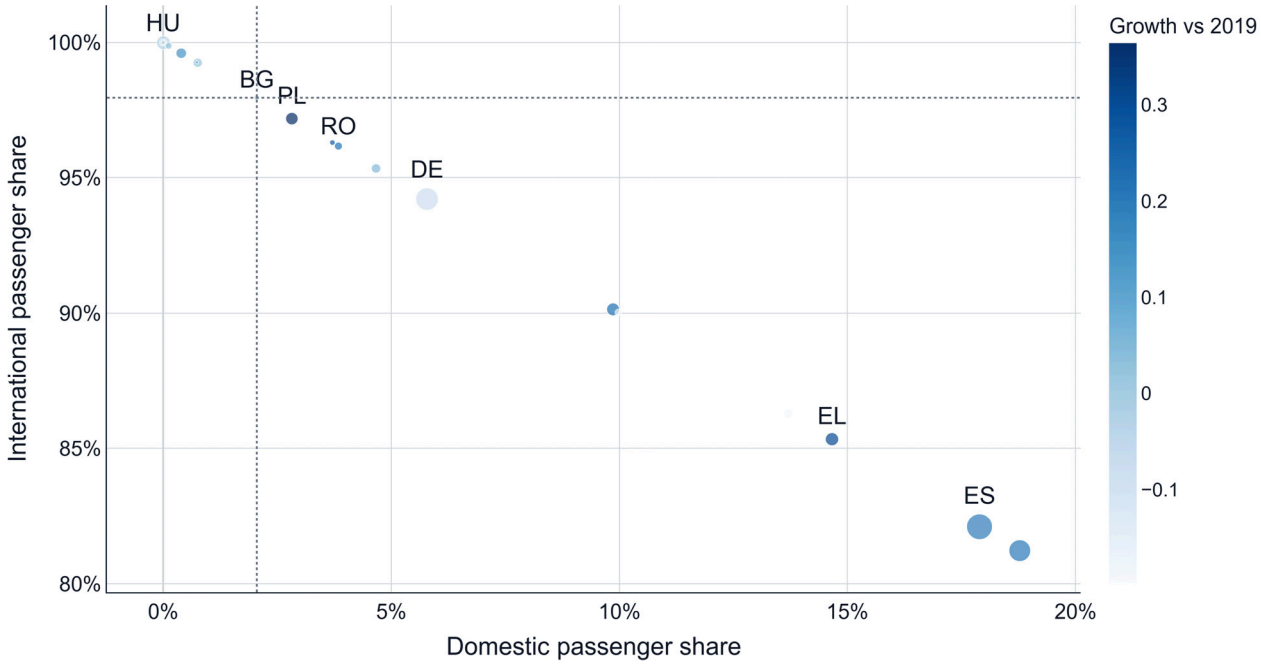

Figure 12. Distribution of international and domestic passenger air flights of EU countries in 2025.

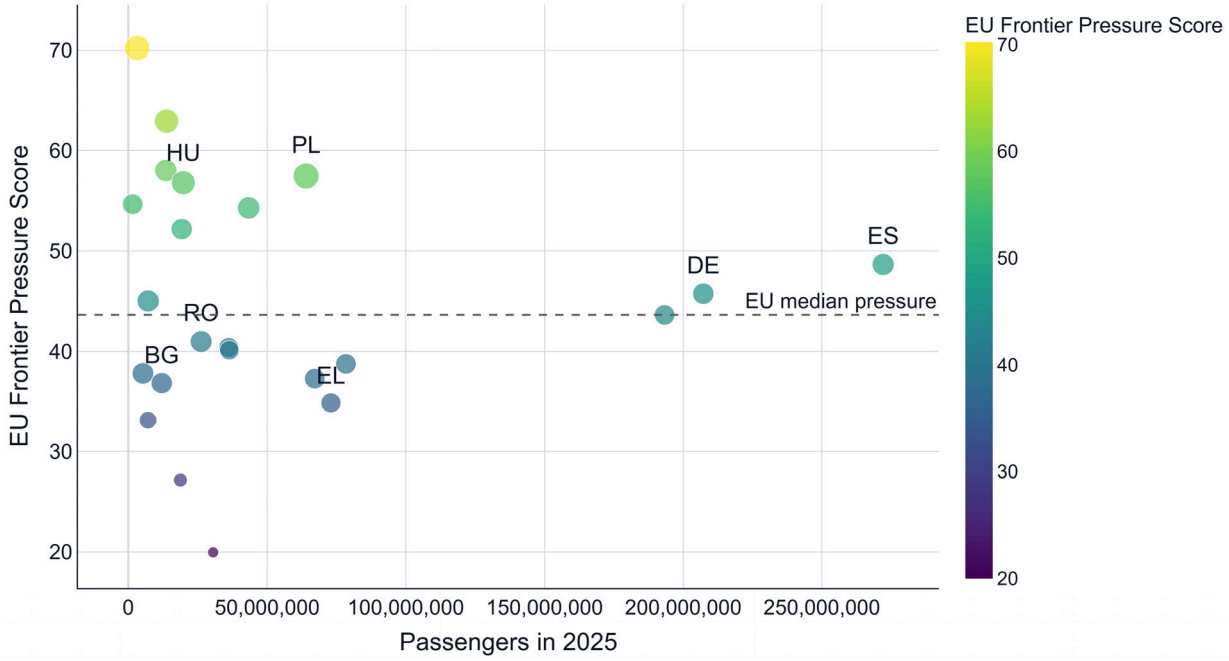

Figure 13. Traffic exposure index and passenger volume for EU23 countries in 2025.

In order to demonstrate the efficiency of boarding methods, an evaluation according to the academic literature by calculating the total number of minutes that could have been saved by integrating a specific boarding method was performed. Figure 14 presents the total minutes that could have been saved by integrating the WILMA boarding method. According to researchers, the WILMA method could save a total of 31.8% of the total boarding time, approximately 118 s per flight [21]. Spain is the country that could benefit the most by saving 3,507,720 min, or 58,462 h, followed by Germany with 2,867,139 min, or 47,786 h, while Italy is in third place with 2,586,889 min, or 43,115 h. The Netherlands is in fourth place with 1,045,981 min, or 17,433 h, and Greece is fifth with 998,519 min, or 16,642 h. For Romania, which is in 12th place, a total of 343,842 min could have

been saved in 2025, which represents approximately 5731 h. According to Nyquist and McFadden [39] and Steffen and Hatckiss [17], every minute saved in the boarding process represents approximately USD 30 in savings. In this case, Spain would theoretically save approximately USD 105,231,600 according to the stated assumptions, while Germany could theoretically save around USD 86,014,170 and might save USD 77,606,670 based on the current assumptions. The Netherlands has a potential save of approximately USD 31,379,430, and Greece has an estimated savings of USD 29,955,570, while Romania could have saved around USD 10,315,260 in theory.

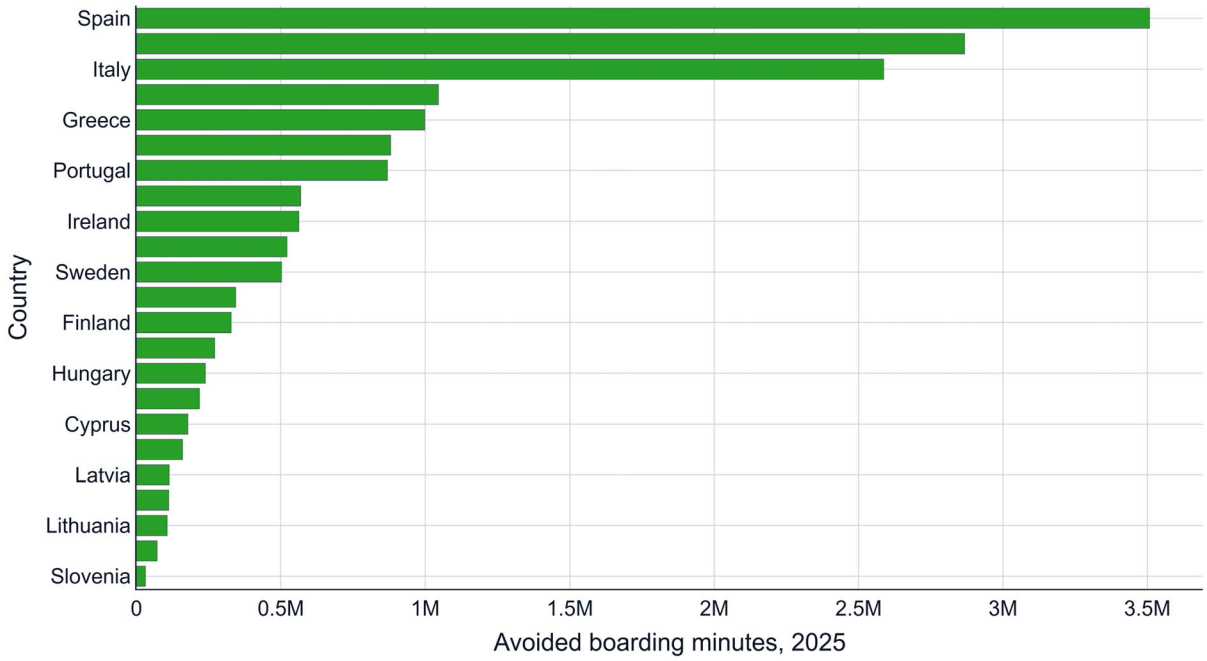

Figure 14. Total avoided boarding minutes per country in 2025 by using the WILMA method. Note: The monetary values represent gross theoretical estimations, excluding technological implementation, passenger communication and staff training costs, and they should not be considered as airline realized savings.

The optimized Steffen boarding method stands as one of the best techniques according to the academic literature, saving approximately 41.8% of the total boarding time, which represents 155 s per flight [17]. In Figure 15, the time savings that could have been achieved if all flights from EU countries had integrated the optimized Steffen technique are presented. Spain is the first due to its highest number of flights, having a potential save of 4,607,599 min, or 76,793 h, representing USD 138,227,970. Germany has a potential save of 3,766,158 min, or 62,769 h, representing approximately USD 112,984,740. Italy, in third place, has a potential save of 3,398,033 min, or 56,634 h, which sums up to a total savings of USD 101,940,990. The Netherlands has a potential save of 1,373,959 min, or 22,899 h, which means around USD 41,218,770, and Greece has a potential save of 1,311,615 min, or 21,860 h, being equivalent to USD 39,348,450. Romania, once again, is in 12th place, with a potential save of 451,657 min, or 7528 h, which represents USD 13,549,710.

The saving time achieved using the reverse pyramid boarding method is shown in Figure 16. Using the researchers' analysis regarding the boarding methods, approximately 20.0% of time could have been saved, or approximately 74 s per flight [37]. The country with the highest potential of time saving is Spain, which could save around 2,205,702 min, or 36,762 h, representing USD 66,171,060 that could have been saved, followed by Germany with 1,802,896 min, or 30,048 h, which is equivalent to a potential save of USD 54,086,880, while Italy had a potential save of 1,626,671 min in 2025, or 27,111 h, representing USD

37,850,130. The Netherlands is in fourth place with approximately 657,727 min, or 10,962 h, or around USD 19,731,810, while Greece is fifth with a potential time saved of 627,883 min, or approximately 10,465 h, and a potential save of USD 18,836,490. Romania is in 12th place, having a potential time saving of 216,213 min, or 3604 h, representing a potential save of approximately USD 6,486,390.

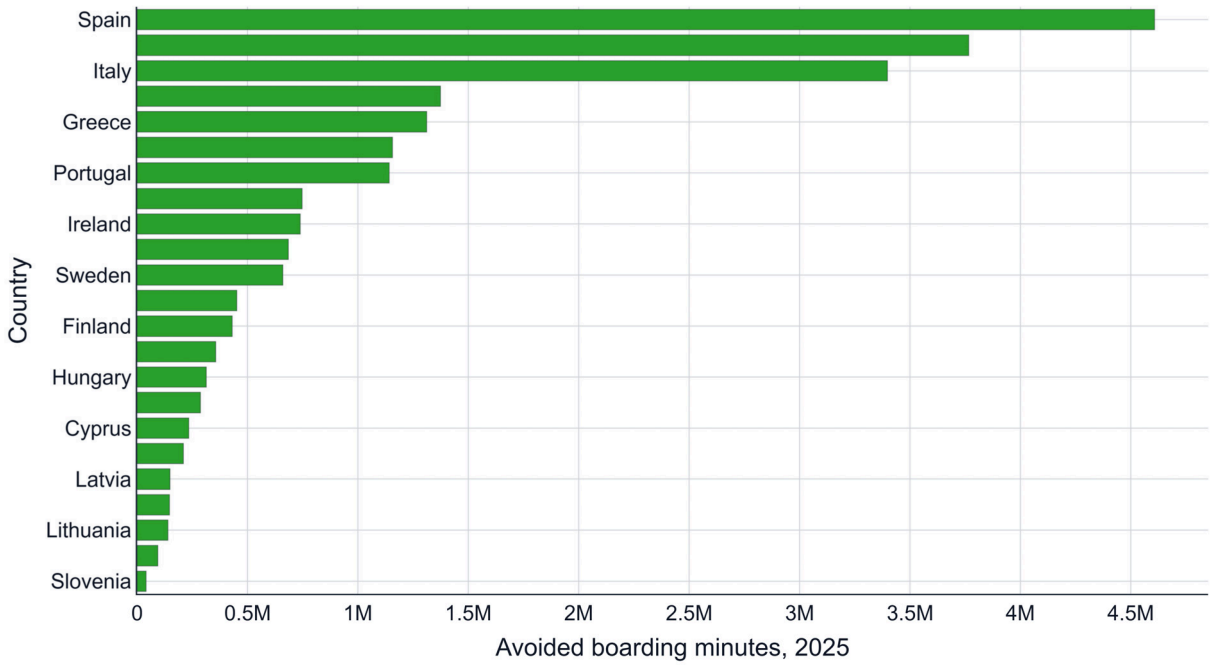

Figure 15. Total avoided boarding minutes per country in 2025 by using optimized Steffen method. Note: The monetary values represent gross theoretical estimations, excluding technological implementation, passenger communication and staff training costs, and they should not be considered as airline realized savings.

The saving time achieved using individual stochastic boarding assignment is included in Figure 17 for EU countries. According to the academic literature, the total savings are approximately 25.0%, which represents 93 s saved per flight [18].

Spain is the country with the highest potential number of minutes saved with approximately 2,757,128 min, or 45,952 h, which represents USD 82,713,840, followed by Germany with 2,253,621 min, or 37,560 h, or around USD 67,608,630, while Italy is third with 2,033,339 min, or 33,889 h, having a potential save of USD 61,000,170. The Netherlands is fourth with 822,159 min, or 13,703 h, which represents a potential saving of USD 24,664,770, and Greece is fifth with 784,854 min, or 13,081 h, or a potential save of approximately USD 23,545,620. In this case, Romania is in 12th place with a potential saving of 270,266 min in 2025, or approximately 4504 h, being equivalent to USD 8,107,980.

In the study done by Milne and Kelly [16], the assigned-seat technique led to a theoretical minimization of around 165 s per boarding process, representing a savings of approximately 44.4% compared to the reference technique utilized in their investigation. In Figure 18, the values are transferred to the scenarios that were tested, pointing out the potential minutes saved theoretically based on the Milne and Kelly assumptions.

Spain is the country with highest number of potential minutes saved, with a total of 4,892,973 min, or 81,550 h, which represents a potential saving of around USD 146,789,198, followed by Germany with 3,999,417 min, or 66,657 h, or approximately USD 119,982,518, while Italy could save 3,608,491 min, or 60,142 h, or USD 108,254,749. In fourth place is the Netherlands with a potential save of 1,459,055 min, or 24,318 h, having a potential saving of USD 43,771,676, and Greece is fifth with 1,392,850 min, or 23,214 h, or approximately USD

41,785,520. Romania is in 12th place with a potential save of 479,631 min, which represents approximately 7510 h, or USD 14,388,925.

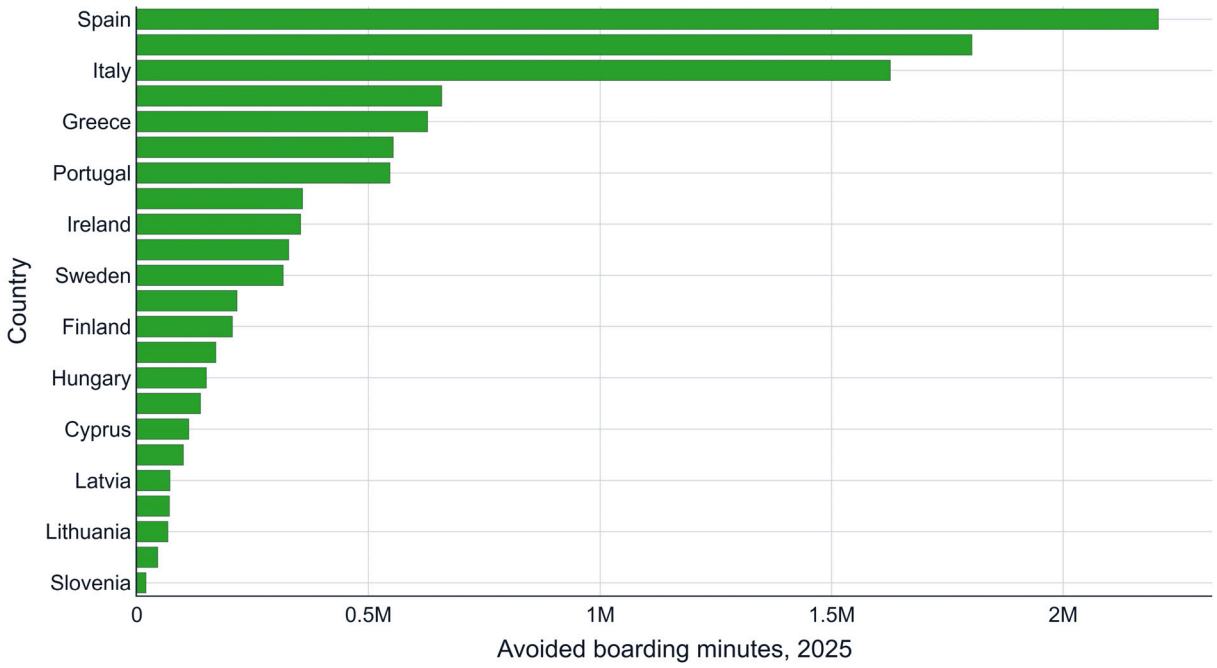

Figure 16. Total avoided boarding minutes per country in 2025 by using reverse pyramid method. Note: The monetary values represent gross theoretical estimations, excluding technological implementation, passenger communication and staff training costs, and they should not be considered as airline realized savings.

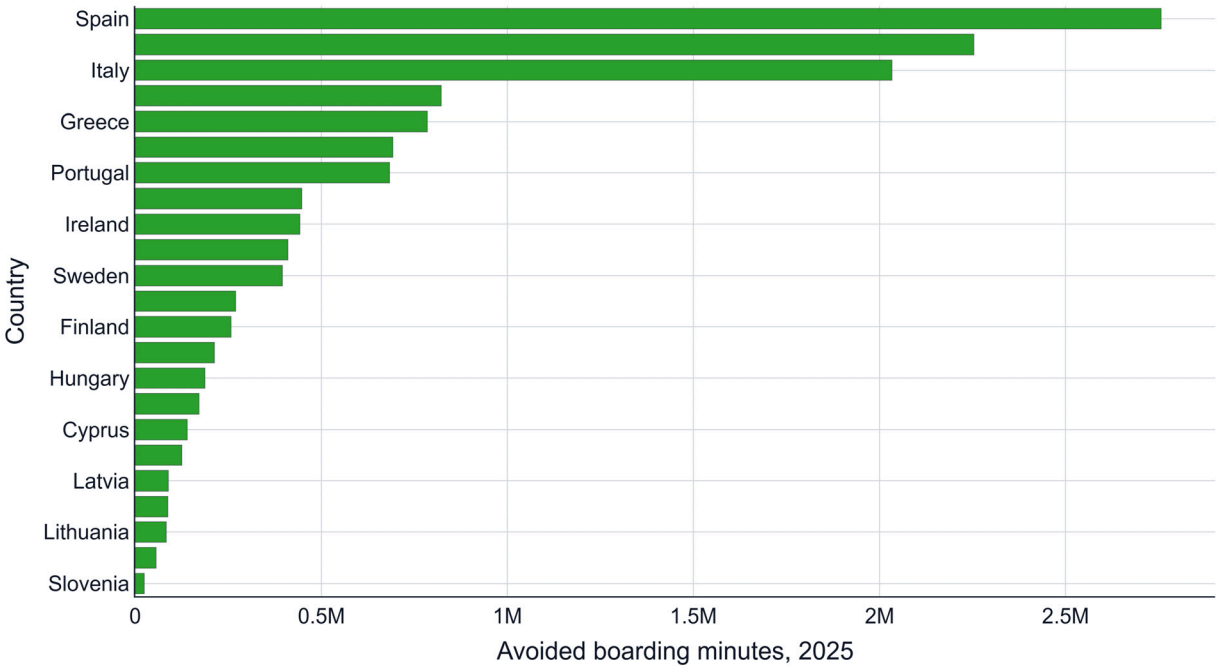

Figure 17. Total avoided boarding minutes per country in 2025 by using the individual stochastic boarding assignment method. Note: The monetary values represent gross theoretical estimations, excluding technological implementation, passenger communication and staff training costs, and they should not be considered as airline realized savings.

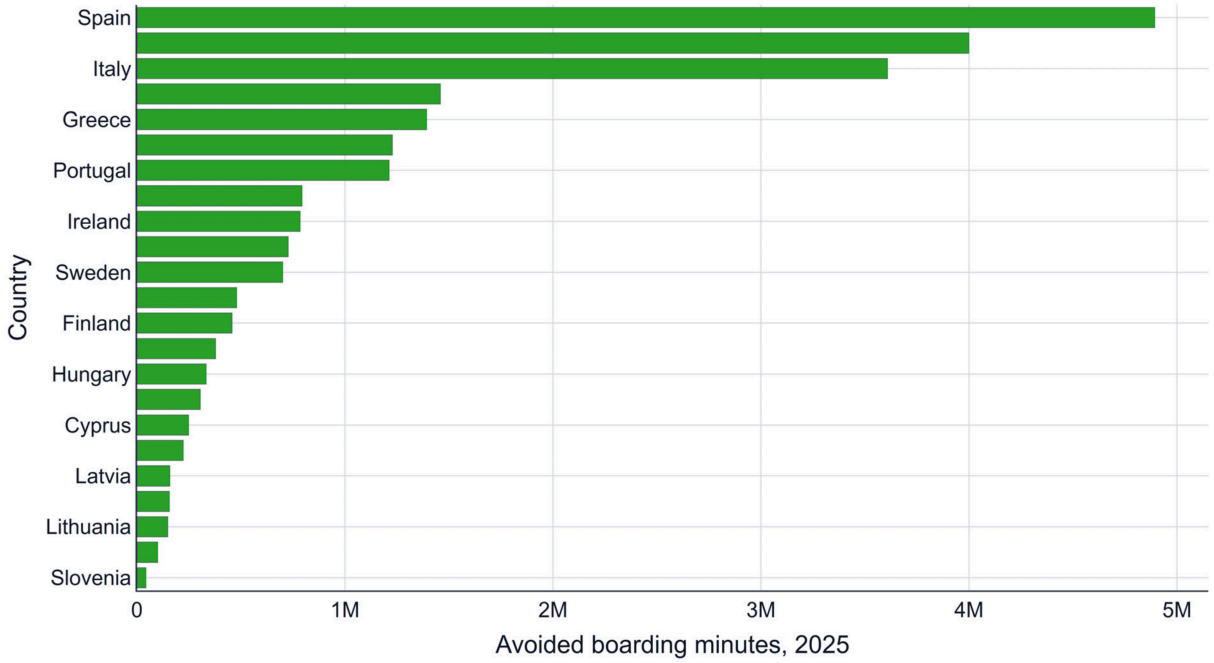

Figure 18. Total avoided boarding minutes per country in 2025 by using assigned-seat method. Note: The monetary values represent gross theoretical estimations, excluding technological implementation, passenger communication and staff training costs, and they should not be considered as airline realized savings.

The annual distribution of avoided boarding minutes based on boarding techniques is described in Figure 19. All methods have three outlier values which represent the biggest three countries, Spain, Germany and Italy. The first technique is WILMA, which has a minimum boarding time saving of 31,126 min (Slovenia), while the first quartile shows that 25% of the values are lower than 164,318 min (including Bulgaria, Latvia, Luxembourg, Lithuania, Slovakia and Slovenia). The median value is 343,842 min, which shows that 50% of the values are lower, including countries like Romania, Finland, the Czech Republic, Hungary, Croatia, and Cyprus, plus the ones already presented above. The third quartile expresses that the remaining 25% of the values are higher than 1,152,904 min, which is the quartile value and is not included for countries like the Netherlands, Italy, Germany and Spain, while the rest of the countries are included in the third quartile.

The maximum value is 1,045,981, which is equivalent to the Netherlands' minutes saved. For the rest of the boarding methods, the approach is similar: all quartiles include the same countries, having just the minimum, the first quartile, the median, the third quartile and the maximum value different. For optimized Steffen, the minimum value is 40,886 min, while the first quartile value is 215,841 min, the median value is 451,657 min, while the third quartile value is 1,152,904, and the maximum value is 1,373,959 min. The reverse pyramid has a minimum value of 19,572 min, the first quartile value is 103,325 min, the median value is 216,212 min, the third quartile value is 551,906 min, and the maximum value is 657,727 min. The individual stochastic boarding assignment boxplot has a minimum value of 24,466 min, a first quartile value of 129,156 min, a median value of 270,265 min, a third quartile value of 689,883 min, and a maximum value of 822,159 min. The last method analyzed is the Milne–Kelly assigned-seat method, which has a minimum value of 43,419 min, a first quartile value of 229,209 min, a median value of 479,630 min, a third quartile value of 1,224,310 min, and a maximum value of 1,459,055 min.

Figure 19 demonstrates that the assigned-seat technique contributes to the highest theoretical time saving compared to all scenarios tested. The results do not demonstrate

the feasibility level for each technique from an operational perspective. Based on the operational interpretation, WILMA is the most feasible technique since it is easier to implement, communicate and explain to the passengers instead of the assigned-seat sequence method. The boarding process techniques should be understood as scenario estimations not as validated operational results for EU member states and Romania. The assigned-seat method shows the best results theoretically, saving the most minutes during the boarding process according to the existing scientific literature. Due to the potential difficulties during practical implementation, the best theoretical method is not necessarily the easiest or the best to be integrated, relying on passengers' behavior, aircraft types, and gate activities. WILMA stands as a more feasible solution from an operational point of view, and it is, at the same time, easier to explain to passengers, providing sequential boarding, allowing people with window seats to board first, then people with middle seats, and people with aisle seats last, depending significantly on aircraft types, passenger behavior, luggage and gate procedures.

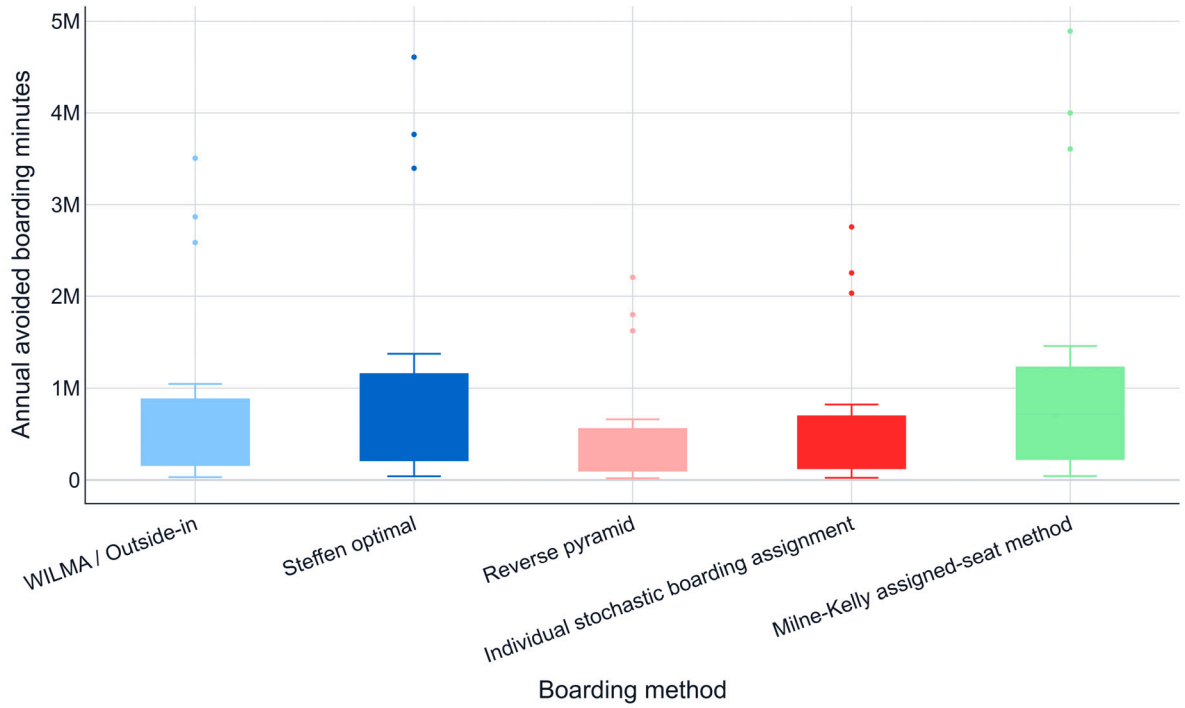

Figure 19. Boxplot for boarding methods and the total avoided boarding minutes across all EU countries.

The technique proposed by Milne and Kelly saves the most theoretical time and costs by applying the same assumptions as the study published by the authors herein. The outcome shows that assigned seat stands as an optimum method compared with the rest of the four methods investigated, but the results do not demonstrate operational feasibility. Therefore, the WILMA method has a smaller theoretical time and cost savings, but it has higher operational feasibility, being simpler to explain to passengers and to implement.

In order to see which algorithm can predict future values as accurately as possible, a back test prediction was done, as shown in Figure 20, by including multiple ML algorithms, such as lasso regression, drift, damped drift, CAGR recovery, exponential smoothing, KNNs, extra trees, SVR, post-COVID CAGR, and log extra trees, and by predicting the 2023, 2024 and 2025 values. In order to see which model had the highest accuracy, several metrics, such as the sMAPE, MAPE, RMSE, MASE, bias and MAE, were calculated for each algorithm and are described in Table 7. For instance, in 2023, the lasso regression

model estimated a value of 15,628,760 passengers, while the drift algorithm predicted 20,357,714 passengers, the post-COVID CAGR predicted 21,880,265 passengers, and log extra trees estimated 18,689,156 passengers, while the real number was 22,964,198 passengers. A similar procedure was carried out for the rest of the models and for the rest of the period analyzed.

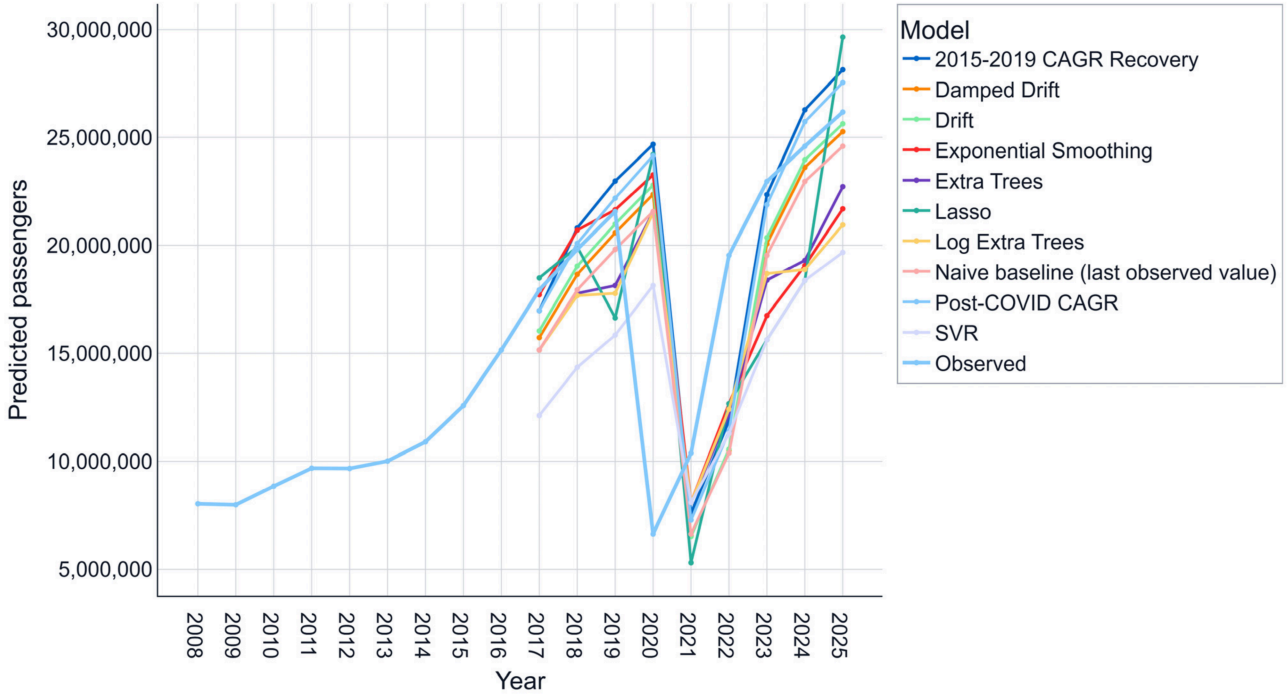

Figure 20. Rolling back test estimations for the algorithms.

In order to check the accuracy of the algorithms, Table 8 contains six different metrics, MAPE, MAE, RMSE, sMAPE, bias and MASE, for all ten ML algorithms. The overall ranking was calculated as an average ranking for each metric. Post-COVID CAGR is the optimal model, which is in first place on four out of six metrics, having a bias value of 3.15%, an sMAPE value of 23.85% and an MASE value of 0.83, while the drift algorithm is in second place, which has an absolute value of 3.05%, an MASE value of 0.87 and an sMAPE value of 26.33%. Ideally, the absolute bias should be 0, but a value closer to 0 points out a strong model that has consistent predictions, quantifying the directional offset. In third place is the 2015–2019 CAGR recovery algorithm, which has an absolute bias value of 5.57% and an MASE value of 0.87, while damped drift is fourth with an absolute bias value of 4.56% and an MASE value of 0.92. The MASE value represents the quality of the algorithm compared to the baseline model, and if the value is below 1, this means that the algorithm beats the baseline model; otherwise, it is worse than the baseline model if the value is higher than 1 or is as good as the baseline model if the value is 1. The naive benchmark is in fifth place, with an sMAPE value of 29.42%, a bias of −7.36% and an MASE value of 1.00. The sMAPE explains the mean error of the predictions and normalizes the results by the mean magnitude of predicted and real data values. A value between 10% and 20% shows good accuracy, while an accuracy between 5% and 10% shows very good accuracy of the algorithm. The rest of the models have values higher than 1 for MASE and an absolute bias higher than 26%, which demonstrates the inaccuracy of the models. In sixth place is exponential smoothing, followed by extra trees, the log extra trees algorithm, and the lasso algorithm, and in last place is SVR.

Table 8. Algorithms' accuracy during back test for three-year period.

Algorithm	MAPE (%)	MAE	RMSE	sMAPE (%)	Bias (%)	MASE	Overall Ranking
Log Extra Trees	40.54	5,078,520	6,235,423	31.01	−11.39	1.17	8
Exponential Smoothing	38.68	4,412,505	6,481,521	26.63	−4.82	1.02	6
SVR	40.26	6,357,382	6,758,647	40.26	−21.97	1.46	10
Lasso Regression	47.96	5,723,522	7,325,530	37.05	−7.46	1.32	9
Drift	37.27	3,795,407	6,102,158	26.33	−3.05	0.87	2
2015–2019 CAGR Recovery	38.39	3,791,138	6,372,765	24.09	5.57	0.87	3
Post-COVID CAGR	37.18	3,601,063	6,260,544	23.85	3.15	0.83	1
Naive Baseline	38.58	4,345,888	5,988,798	29.42	−7.36	1.00	5
Damped Drift	37.72	3,988,075	6,047,486	27.40	−4.56	0.92	4
Extra Trees	39.77	4,868,790	6,104,049	30.08	−10.22	1.12	7

The outcomes described in Table 7 do not confirm that complex algorithms have better accuracy than simple models. Techniques that have an MASE score higher than one for the evaluated period performed worse than the naive base model that was utilized as the benchmark. Due to the limitations of data availability and the COVID-19 pandemic disruption, the risk of overfitting was significant, especially for the KNN, SVR and extra trees models. The standings should be interpreted as exploratory results for the sample data integrated in this research.

A total of five algorithms out of the ten, based on the overall ranking, were trained, as shown in Figure 21, in order to predict the future values for the air passengers that will be carried in the following five years in Romania.

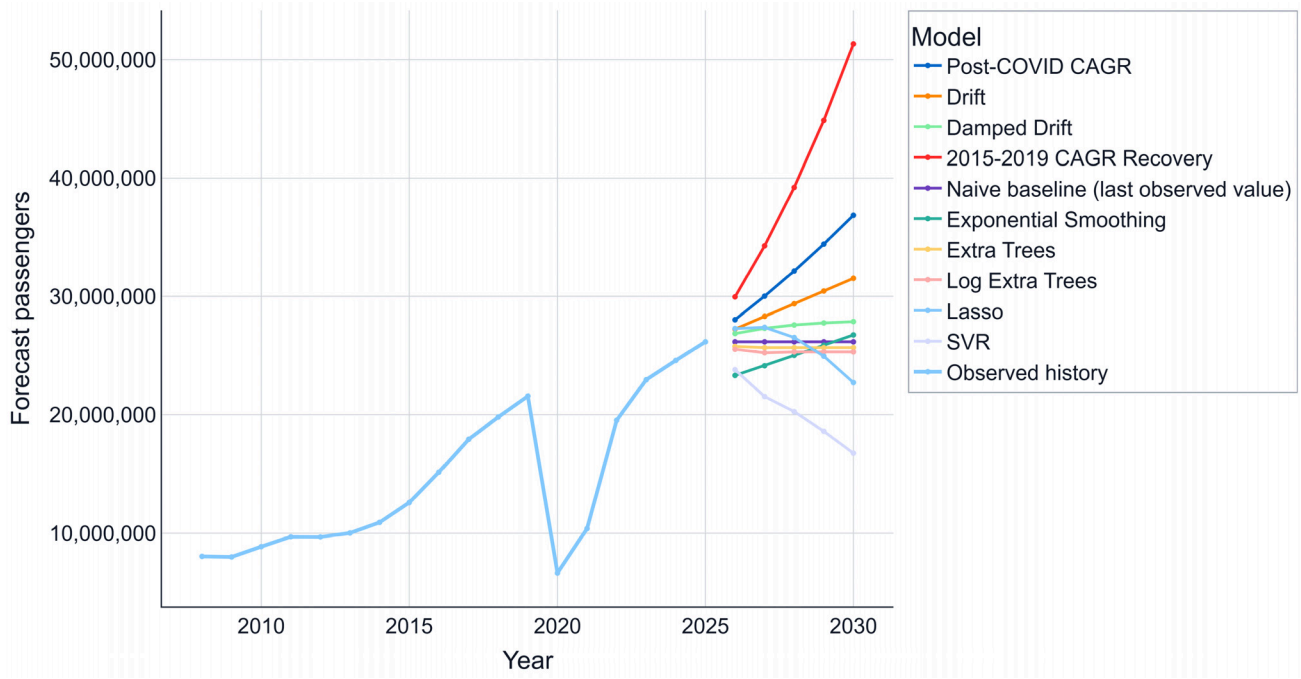

Figure 21. Romanian air passengers' prediction for next five years.

The predictions between 2026 and 2030 are scenario-based estimations. The first model, called the post-COVID compound annual growth rate (CAGR), takes into consideration the average increase that happened between 2022 and 2025. The model predicted a total of 28,028,079 passengers in 2026, achieving a value of almost 37 million passengers in 2030 (36,849,911). The second algorithm that was included in the analysis is the drift algorithm, which estimated a value of 27,242,014 passengers in 2026, and the maximum value was obtained in 2030, achieving a total of 31,511,069 passengers, while the 2015–2019 CAGR recovery scenario estimated a total of 29,950,079 passengers in 2026 and a total of 51,340,450 passengers in 2030. The damped drift algorithm predicted 26,868,472 passengers in 2026, followed by 27,310,623 passengers in 2027, 27,589,286 passengers in 2028, and 27,763,847 passengers in 2029, and the peak was achieved in 2030, with a total of 27,872,874 passengers. The last model included in the analysis is the naive baseline model, which predicted a total of 26,174,751 passengers in the following years. The 2026–2030 estimations stand as an exploratory experiment instead of real predictions. The main purpose of the future predictions is to provide an overview of the trajectories estimated by each algorithm tested.

A clustering of EU member states was done, as shown in Figure 22, in order to see how similar the countries are based on the domestic share, the COVID-19 shock, the passenger volume, and the growth rate between 2025 and 2024 and between 2025 and 2019.

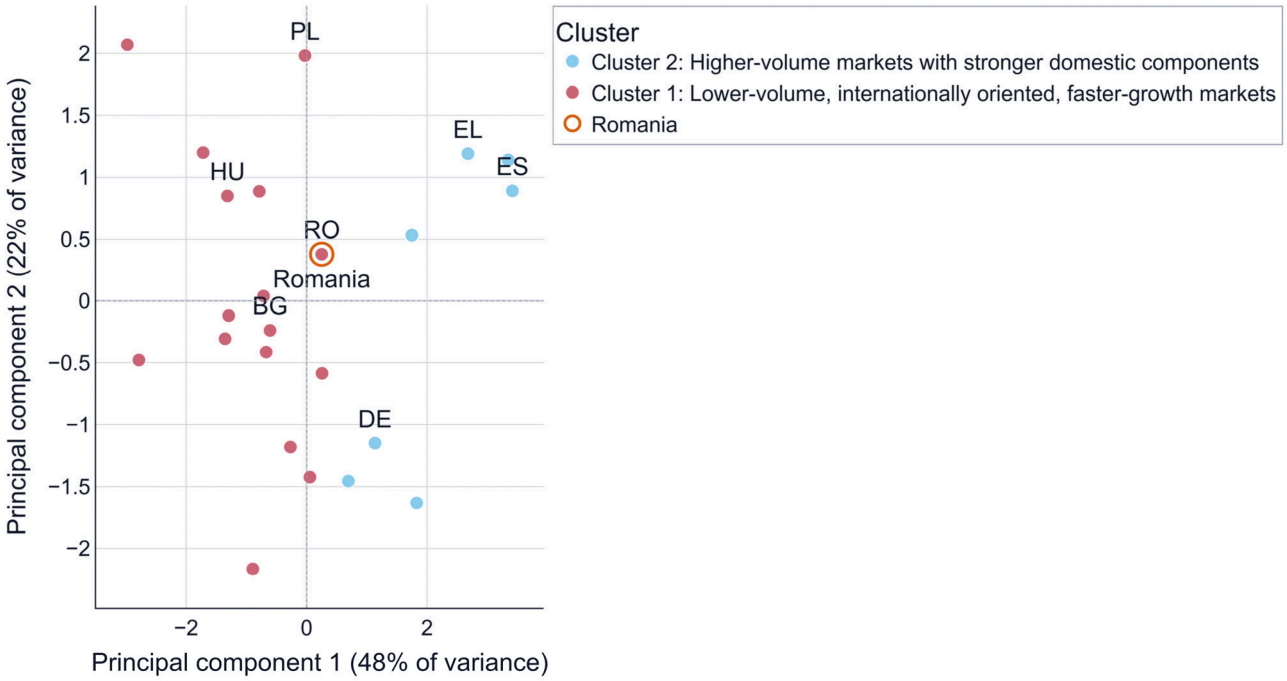

Figure 22. Clustering of EU countries in 2025.

The countries colored red are a part of cluster one, while the countries colored blue are a part of the second cluster. To perform a clustering, a PCA algorithm first needs to be applied to reduce the dimensionality and complexity among the features. Two dimensions have been defined, first including the COVID-19 impact on the airline industry, the passenger volume per country and the domestic share per country, which explains approximately 48% of the variance, referring mostly to the traffic volume and market scale per country, while the second component refers to the growth rate between 2025 and 2024 and between 2025 and 2019, and it explains approximately 21.9% of the variance, referring mainly to the rebound ability of the countries. There are two clusters that were defined. The first includes a total of 16 countries, while the second cluster includes only seven

countries. The first cluster includes Romania, Luxembourg, Lithuania, Ireland, Denmark, Hungary, Croatia, Cyprus, Austria, Bulgaria, the Czech Republic, the Netherlands, Slovenia, Slovakia, Poland and Latvia, while the second cluster includes Spain, Sweden, Finland, Germany, Greece, Portugal and Italy. On average, the number of passengers in cluster one is 24,184,745, having a recovery rate of 10.9%, an international share of 98.8%, a domestic share of just 1.2% and a growth rate between 2025 and 2024 of 7.8% compared with 2019, representing the countries that are on a constant positive trend, especially the emerging countries. Countries in the second cluster are developed member states with a mature economy, which is explained by the high number of passengers on average (123,144,574) but a smaller growth rate between 2025 and 2019 (6.4%) and between 2025 and 2024 (4.6%), with a smaller international share (87.0%) but a higher domestic share (13.0%) that can be clarified by the bigger surface of the countries included in the second cluster compared to the first cluster.

4. Discussion and Limitations

In this fourth section of the analysis, a detailed explanation regarding the existing limitations of this research, together with a discussion of the results, is provided. The investigation incorporates all 27 EU countries into a quantification of the cumulative impact caused by the COVID-19 pandemic between 2020 and 2022, followed by an evaluation of the Romanian national air transportation sector, also including airport-level data and a harmonized comparison using 2025 data for 23 EU member states. In the third section, the focus was on how to integrate the most feasible methods from an operational perspective that minimize costs and facilitate operating activities. Based on the comparison between the 2019 and 2025 number of passengers and that of 2024 and 2025, respectively, together with the traffic exposure index, clear expertise regarding the air transportation sector for each country has been defined, providing an understanding of the density, network size and volume level. All EU countries should check the scan-to-door-close time and boarding duration to define a list with gate types, airlines, aircraft types and cabin-bag interventions in order to better understand how to prioritize the implementation of new methods and technologies.

As was explained during the analysis, Romania is one of the countries that is in continuous expansion, having a positive trend on the number of passengers after the COVID-19 pandemic. It is considered as a medium-sized European network, and because of this, the first measure that should be implemented is to focus on specific flights for boarding time quantification on the biggest airports and to prioritize routes with the highest volume of traffic, followed by automation of the procedures. In order to implement this, an integrated gate procedure and an automated selective process for overcrowded airports and a cabin-bag KPI definition should be established. The rebound level compared to 2019, the traffic exposure index, the passenger scale and the growth rate between 2024 and 2025 represent different ways to establish the operating context, which provides an overview regarding network size and density. Based on network size, various solutions can be found. For instance, medium networks like Romania should focus on gate procedures, automatic selection for gates and reliable traffic measurement, while large networks should focus especially on dynamic sequencing in order to control the peak passenger flow.

Depending on the implementation time and on efficiency, there are multiple techniques that could reduce the boarding time and costs, the observation and recording of D15 activities that refer to timestamps for the boarding-pass scanning process, the total boarding time, the door-close total amount of time and cabin-bag interferences [21,40,41].

The second phase involves the implementation of the WILMA boarding technique for comparable flights and records the gate type, passenger load factor, airline name, and

aircraft type and to alternate boarding with other techniques, such as optimized Steffen, reverse pyramid, individual stochastic boarding assignment, and assigned seat [42,43].

The last activity is to scale exclusively the methods that demonstrate efficiency only if the aircraft type, airline companies and passenger flows are not affected, if there are no complaints and delays, and if the boarding time is improved [12,43].

All EU member states can improve the boarding time, which will generate costs and save time. An integration of multilingual boarding calls can facilitate the boarding process in a significant manner, especially for the most frequent routes. According to the academic literature, the WILMA boarding method represents an optimal technique that can match the aircraft and load factor levels from all EU member states by assigning seat positions and board passengers in batches in order to minimize interference. Optimized Steffen also represents a strong boarding method that can save significant time and money, but it requires specific techniques to perform at its best [17]. Based on the airline company, cabin size and passenger type, other boarding methods can be efficient [9]. At the same time, it is necessary to observe and note the level of seat interference, the group of passengers, cabin-bag stowage and aisle conflicts [10,44].

When a flight has a total number of passengers that exceeds the median level, it is necessary to identify the patterns of group or family members, where the carry-on luggage is stored in order to provide the optimal pre-gate luggage checking procedure and to board the family or group members together [45]. The integration of the boarding process and the turnaround critical path stands as another factor that could lead to a potential time and cost saving by connecting the boarding completion process with gate occupancy and to accomplish the D0/D15 metrics, which refer to departure punctuality and operational performance [8,11,15].

The analysis utilized three data samples, one for the quantification of cumulative impact cause by the COVID-19 pandemic disruption between 2020 and 2022 for all 27 EU countries, the AAR Romanian national and airport-level exploration, and the comparative analysis of 23 EU member states for 2025 data.

A detailed analysis and comparison between Romania and EU was done by evaluating the absolute passenger increase between 2008 and 2025, the year-over-year change in Romania, the passenger distribution among Romanian airports, the prediction of future values, and the clustering of countries, defining the Romanian profile compared to the EU median and the EU average and the boarding time and cost savings per boarding method included in the analysis.

The existing differences in the post-pandemic rebound are not exclusively due to the increase in low-cost airline routes, tourism, or labor mobility. Between 2020 and 2022, the EU member states had different border and traveling restrictions and quarantine and testing obligations. Countries that dropped the restrictions earlier benefited from an increase in the number of passengers, which led to a faster rebound, which is independent of market attributes. The data that was utilized in this research does not refer to the severity of restrictions or timing for the 2020–2022 period, and it is impossible to isolate or differentiate the impact of restrictions, migration, low-cost company expansion and tourism, and the outcomes should be understood as a descriptive investigation of multiple national rebound predictions. The results therefore stand as a descriptive exploration at the national rebound level instead of a causal prediction of their main factors.

The Romanian passenger evolution could be correlated with tourism, income growth, labor mobility, regional development or low-cost company expansion. At the same time, the extracted datasets do not include variables related to the factors presented earlier; therefore, the outcome should be understood as a theoretical descriptive exploration. This research shows that the Romanian air transportation sector is still concentrated mainly on

the Henri Coandă International Airport, according to the number of passengers carried per airport, but it does not point out inefficiency regarding operational activities of the airports.

The AAR and Eurostat are two separate data sources that are not interchangeable, due to their differences in time reporting, procedures and validations. Eurostat was utilized exclusively for the Romania–EU member state comparison, while the AAR data was utilized to explore the national and airport-level evolution of the Romanian air transportation sector.

This research does not include country-level data metrics harmonized in order to quantify the impact of quarantine or testing restrictions or border closing and reopening periods; therefore, the existing differences cannot be explained mainly by market attributes.

The boarding process is part of a wider component related to airplane turnaround and passenger handling. This study does not quantify the full handling process or the interaction of all operational activities; it predicts the gross theoretical cost savings instead of promoting realized savings or improvements. In order to validate the outcomes, it is mandatory to replicate the analysis using real flight-level data that includes the duration of boarding procedures, airplane types, fuel consumption, load factors, and luggage handling durations.

Operational activities depend on boarding processes, which depend on the turnaround critical path, and it is mandatory to complete remaining activities, such as catering, luggage handling and refueling, in order to have an earlier departure. If passenger boarding delays the departure of a flight, there is a potential to increase efficiency, minimize gate occupancy and maximize the airplane utilization rate [8,9,21]. The high concentration of passengers in Romania, especially in the Henri Coandă International Airport, can lead to potential risks due to the constant increase in traffic flow. The operational outcome of a faster boarding process relies on the critical turnaround path, since boarding can be completed faster than fueling, cleaning, catering or baggage loading, which in the end would lead to delays. When the boarding process delays aircraft door closing, there is a potential improvement which could lead to a faster departure and a minimization in gate occupancy and airplane utilization in the end [8–10,45]. An increase in costs depends on the turnaround critical path, and if the aircraft preparation activities before flight are done after the boarding process is finished, the turnaround time and costs will increase. As was presented above, the theoretical savings depend on the number of passengers, load factors, type of the aircrafts, passengers' behavior and boarding procedures, and the results should be interpreted as illustrative potential savings for Romania, with WILMA representing one of the techniques that saves a significant amount of time and costs, and it is feasible from an operational point of view compared to the assigned-seat and Steffen boarding procedures, which are difficult to be implemented in reality. WILMA provides a minimization in seat interference and minimal interaction between staff and passengers. For the Romanian case, the results could be validated based on a comparison analysis between the same parameters, namely aircraft type, number of passengers, and load factor; the same gate procedures; and similar departure times by calculating the total boarding process between the WILMA and assigned-seat or Steffen boarding techniques.

Passenger growth should be understood as a metric that expresses the potential improvement in operational activities, not automatically as a boarding inefficiency method. At the same time, the increasing number of passengers does not mean that there will be more congestion at the gates or high costs for the companies or higher turnarounds, but it could generate pressure on airport infrastructure at some point, such as the capacity of luggage and passenger processing, gate allocation, air company fleet allocation or terminal capacity, especially during peak periods, where the traffic is higher than expected. During the conducted research, the boarding process was considered relevant only when the turnaround was close to reaching the critical path, and in this way, boarding techniques could minimize

operational exposure by reducing the turnaround time and costs. The volume of passengers stands as an operational exposure metric that could facilitate the quantification of boarding inefficiency, and it is relevant to also mention that the analysis exclusively included concentration and traffic measures that helped find the most urgent operational processes that should be fixed in the future, not to define and point out boarding inefficiency.

The analysis should be considered as a prioritization tool rather than a direct measurement of the total boarding time and costs, which need operational data from airports and flights, together with the departure and arrival time, the load factor, the number of staff members per flight, the boarding technique and the gate occupation time.

The rebound in the post-pandemic span of passenger numbers is not necessarily equivalent to the recovery of airport or regional markets, since a significant number of employees were fired or left the industry due to the severe restrictions. The recruitment and training of new employees require time and resources and generate costs that could affect the operational activities of air transportation companies and airports. The limited personnel could have had a significant impact on travelers and luggage handling or the quality of services. The data that was collected and utilized in the analysis does not contain information regarding training costs, periods, employees' qualifications, and staff shortages. The factors previously presented are relevant for this research but, due to the limitations of existing datasets, were not included in the exploratory and quantitative investigations.

The rollback predictions should be considered as the best algorithms within the tested ones, not as the best model among all the existing ones. The post-COVID CAGR scenario obtained the best average results on all six indicators, but the error is still significant, performing better than the naive algorithm. At the same time, the bias metric should be distinguished by the overall estimation error since bias estimates the cumulative predictive error.

This research has limitations. The main limitation is the limited data availability for the EU and Romania since the reporting is different from one country to another. The best example is the exclusion of Belgium, Malta, France and Estonia for the 2025 analysis, together with the usage of a single dataset for the EU data, from Eurostat, while for Romania, the national AAR website was also used. The lack of information for 2025 led to the omission of Belgium, France, Malta and Estonia from the 2025 investigation, limiting the exploration to 23 countries. France is one of the most relevant countries in the air transportation sector, due to its size of market. Nonetheless, the countries were included in the 2024 analysis and in the 2020–2022 cumulative impact of the COVID-19 pandemic disruption. This limitation was applied only for the 2025 comparison analysis, not for the whole research. The data extracted from both sources is not identical due to the different reporting timings, with Eurostat standing as a solid data source for a comparative analysis, while the AAR is suitable for a detailed exploration of the Romanian air transportation sector. The second limitation is the exclusive utilization of EU countries; thus, the findings can represent a benchmark for developed countries but are not diverse enough to include underdeveloped countries, and it can be difficult to replicate the integration of the methods for some countries.

The investigation explores boarding procedures, which are one of the main activities of the air transportation sector, but it does not quantify the complete interaction of all parallel operational activities. Therefore, the predicted potential boarding and cost savings stand as gross theoretical reductions rather than realized savings. It is necessary to validate the results based on flight-level data, which should also contain data regarding boarding durations and costs, together with the load factor levels, luggage volumes, airplane types and cabin configurations. The costs and time saved are theoretical results, since there is no available data for parallel activities, such as refueling, cleaning or luggage handling.

The empirical validation that should be performed was described in the Methodology, Discussion and Limitations Sections.

A significant limitation represents the lack of flight-level operational datasets regarding gate occupancy, airplane types, load factor levels, luggage volumes, boarding durations and cabin configurations, and this study could not determine if boarding was on the critical path or not. At the same time, the monetary outcomes should be taken into account as gross theoretical simulations instead of real air companies' potential savings, due to the lack of training, communication and technological cost values.

The fourth limitation is the exclusive integration of the Python 3.14 programming language, which can integrate specific graphical representations which may not cover the entire perspective of the air transportation sector, together with the integration of a part of ML algorithms or boarding methods and the exclusion of other algorithms or boarding techniques. This can represent a limitation since there can be models that could lead to better results.

The fifth limitation is the focus of the analysis, which explores only quantitative evaluations of the air transportation sector, such as the yearly passenger evolution, the comparison between passenger levels per country, the prediction of ML models, the clustering of countries and the estimation of time reductions in the boarding process reported in seconds.

5. Conclusions

The analysis explored the evolution of the Romanian air passenger sector in the EU determined the theoretical boarding techniques that minimize the time and costs by comparing a total of five methods extracted from academic papers. According to the AAR data, the Romanian air transportation domain evolved from a total of 8.42 million passengers registered in 2008 to 28.55 million passengers registered in 2025. Due to the COVID-19 pandemic, a significant shortfall was registered in the global economy, especially on-air passenger transportation, with Romania facing a decrease of 69.1% compared to 2019. This outcome presents the development and threats of the air transportation sector, and it should not be considered as proof of boarding inefficiency. The outcomes demonstrate that Romania showed a strong positive trend regarding the number of passengers, and according to the national AAR dataset, the number of passengers increased from 8,416,394 passengers in 2008 to 28,547,056 in 2025. According to the potential of time and savings, the method published by Milne and Kelly obtained the best results, but due to the limited operational and integration feasibility, WILMA provides a better balance between theoretical time and cost savings and feasibility implementation. The analysis provides a clear difference between the preferred technique to be integrated and the optimal technical solution. Similar with the rest of the EU countries, Romania was seriously affected by the COVID-19 pandemic, showing a decrease of 69.1% in 2020 compared to 2019:

- Amid the boarding techniques that were extracted from papers from the academic community, the assigned-seat method provides a total savings of 164.6 s, or approximately 165 s per eligible flight, according to the evaluation of Milne and Kelly, representing the optimum one for theoretical expenses and potential time savings, but is limited from an operational feasibility perspective. For Romania, it represents a potential save of 479,631 min and a gross theoretical save of USD 14,388,925. WILMA is simpler to be implemented from an operational point of view, thanks to its passenger communication and implementation, which are much simpler and faster, according to the information extracted from academic papers, since feasibility was not quantified in this research. At the same time, the monetary values stand as gross theoretical values that were estimated for a specific number of eligible flights and with an average of

USD 30 per minute, which does not represent realized savings for air transportation companies. The impact of boarding procedures relies on the critical turnaround path and whether parallel activities, like cleaning, refueling or luggage handling, are delayed or not. The results obtained should be validated on real flight-level data that includes information regarding the airplane type, turnaround time, boarding duration, luggage volume, load factor level and fuel consumption.

- Taking into consideration the first scientific question, Romania had an immediate impact of 69.1% in 2020 regarding passenger traffic caused by the COVID-19 pandemic disruption compared to the last pre-pandemic year (2019) based on the AAR dataset. The disruption continued in 2021 and partially in 2022, and over the three-year period, Romania had a total passenger shortfall of 28.14 million passengers compared to the average 2019 number of passengers utilized as a mean for all three years, representing approximately 43.5% of the three-year benchmark. The difference between the rebound level of Romania and EU member states should be understood as a descriptive evaluation since there is no available information regarding the labor mobility, tourism, low-cost company expansion or travel restrictions for each EU country.
- The assigned-seat method proposed by Milne and Kelly leads to the best theoretical results regarding the boarding time and cost savings, leading to a potential saving of 165 s per flight. This outcome does not take into consideration the feasibility of the methods. According to the exploration that was done and taking academic papers into consideration, WILMA stands as a simple operational technique compared to the assigned-seat method, but the investigation does not include an empirical calculation for feasibility level. All savings that were calculated using experimental scenarios represent theoretical results that should be validated on real flight-level data.
- The Romanian air transport domain showed a positive trend between 2008 and 2025, apart from the COVID-19 pandemic period, which created a strong disruption. In 2008, the passenger traffic in Romania was 8.42 million, while in 2024, the number of passengers was 25.43 million, and in 2025, the peak was achieved, with a total of 28.5 million. The capacity to rebound and the long-term evolution was stronger than most of the EU member states. The growth in passenger numbers should be interpreted as an evolution of the market and operational exposure, not as a threat to air transportation infrastructure.

Future research should focus on gathering and validating flight-level data points, verify if the boarding process is on a critical turnaround path and check parallel activities, such as cleaning, fueling and luggage processing, and how those processes can be an impediment and how to minimize their interference.

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References

1. Suau-Sanchez, P.; Voltes-Dorta, A.; Cugueró-Escofet, N. An Early Assessment of the Impact of COVID-19 on Air Transport: Just Another Crisis or the End of Aviation as We Know It? *J. Transp. Geogr.* **2020**, *86*, 102749. [CrossRef] [PubMed]
2. Gudmundsson, S.V.; Cattaneo, M.; Redondi, R. Forecasting Temporal World Recovery in Air Transport Markets in the Presence of Large Economic Shocks: The Case of COVID-19. *J. Air Transp. Manag.* **2021**, *91*, 102007. [CrossRef] [PubMed]
3. Dobruszkes, F. New Europe, New Low-Cost Air Services. *J. Transp. Geogr.* **2009**, *17*, 423–432. [CrossRef]
4. AAR Arhive Air Traffic in Romania. Available online: https://www.airportaar.ro/category/trafic-aerian (accessed on 16 June 2026).
5. Gil-Rodrigo, S.; Zanin, M. Low Cost Carriers Induce Specific and Identifiable Delay Propagation Patterns: An Analysis of the EU and US Systems. *IEEE Access* **2024**, *12*, 75323–75336. [CrossRef]
6. Dragan, A. Romania and MSCI's New Classification Framework: A Step Forward or a Longer Wait? Available online: https://business-review.eu/money/stock-exchange/romania-and-mscis-new-classification-framework-a-step-forward-or-a-longer-wait-286588 (accessed on 16 June 2026).
7. Asociația Aeroporturilor din România. Available online: https://www.airportaar.ro/category/noutati (accessed on 16 June 2026).
8. Schultz, M. Fast Aircraft Turnaround Enabled by Reliable Passenger Boarding. *Aerospace* **2018**, *5*, 8. [CrossRef]
9. Jaehn, F.; Neumann, S. Airplane Boarding. *Eur. J. Oper. Res.* **2015**, *244*, 339–359. [CrossRef]
10. Hutter, L.; Jaehn, F.; Neumann, S. Influencing Factors on Airplane Boarding Times. *Omega* **2019**, *87*, 177–190. [CrossRef]
11. Neumann, S. Is the Boarding Process on the Critical Path of the Airplane Turn-Around? *Eur. J. Oper. Res.* **2019**, *277*, 128–137. [CrossRef]
12. Van Landeghem, H.; Beuselinck, A. Reducing Passenger Boarding Time in Airplanes: A Simulation Based Approach. *Eur. J. Oper. Res.* **2002**, *142*, 294–308. [CrossRef]
13. Graham, A. *Managing Airports*, 2nd ed.; Routledge: London, UK, 2012; ISBN 978-0-08-047328-4.
14. IATA. Airport Development Reference Manual (ADRM). Available online: https://www.iata.org/en/publications/manuals/airport-development-reference-manual/ (accessed on 28 June 2026).
15. Breaking, T.N. Wizz Air Strengthens Its Position as Europe's Reliable Airline with Strong Operational Performance. Available online: https://www.breakingtravelnews.com/news/article/wizz-air-strengthens-its-position-as-europes-reliable-airline-with-strong-o/ (accessed on 25 June 2026).
16. Milne, R.J.; Kelly, A.R. A New Method for Boarding Passengers onto an Airplane. *J. Air Transp. Manag.* **2014**, *34*, 93–100. [CrossRef]
17. Steffen, J.H.; Hotchkiss, J. Experimental Test of Airplane Boarding Methods. *J. Air Transp. Manag.* **2012**, *18*, 64–67. [CrossRef]
18. Schultz, M. Implementation and Application of a Stochastic Aircraft Boarding Model. *Transp. Res. Part C Emerg. Technol.* **2018**, *90*, 334–349. [CrossRef]
19. Eurostat Air Passenger Transport by Type of Schedule, Transport Coverage and Country. Available online: https://ec.europa.eu/eurostat/databrowser/view/avia_paoc/default/table?lang=en (accessed on 16 June 2026).
20. Eurostat Air Passenger Transport by Type of Schedule, Transport Coverage and Main Airports. Available online: https://ec.europa.eu/eurostat/databrowser/view/AVIA_PAOA/default/table?lang=en (accessed on 16 June 2026).
21. Steffen, J.H. Optimal Boarding Method for Airline Passengers. *J. Air Transp. Manag.* **2008**, *14*, 146–150. [CrossRef]
22. Sun, X.; Wandelt, S.; Zhang, A. On the Degree of Synchronization between Air Transport Connectivity and COVID-19 Cases at Worldwide Level. *Transp. Policy* **2021**, *105*, 115–123. [CrossRef] [PubMed]
23. Chai, T.; Draxler, R.R. Root Mean Square Error (RMSE) or Mean Absolute Error (MAE)?—Arguments against Avoiding RMSE in the Literature. *Geosci. Model Dev.* **2014**, *7*, 1247–1250. [CrossRef]
24. Hyndman, R.J.; Koehler, A.B. Another Look at Measures of Forecast Accuracy. *Int. J. Forecast.* **2006**, *22*, 679–688. [CrossRef]
25. Tashman, L.J. Out-of-Sample Tests of Forecasting Accuracy: An Analysis and Review. *Int. J. Forecast.* **2000**, *16*, 437–450. [CrossRef]
26. Jan, A.K.; Dubes, R.C. Algorithms for Clustering Data. Available online: https://www.scirp.org/reference/referencespapers?referenceid=2060572 (accessed on 16 June 2026).
27. Verma, A. *The Complete Unsupervised Learning Handbook: ML Algorithms*; Medium: San Francisco, CA, USA, 2025.

28. MacQueen, J. Some Methods for Classification and Analysis of Multivariate Observations. In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Statistics*; University of California Press: Berkeley, CA, USA, 1967; Volume 5.1, pp. 281–298.
29. Jolliffe, I.T.; Cadima, J. Principal Component Analysis: A Review and Recent Developments. *Philos. Trans. A Math. Phys. Eng. Sci.* **2016**, *374*, 20150202. [CrossRef] [PubMed]
30. Hyndman, R.J.; Koehler, A.B.; Snyder, R.D.; Grose, S. A State Space Framework for Automatic Forecasting Using Exponential Smoothing Methods. *Int. J. Forecast.* **2002**, *18*, 439–454. [CrossRef]
31. Verma, N. *An Introduction to Support Vector Regression (SVR) in Machine Learning*; Medium: San Francisco, CA, USA, 2023.
32. Hastie, T.; Tibshirani, R.; Tibshirani, R. Best Subset, Forward Stepwise or Lasso? Analysis and Recommendations Based on Extensive Comparisons. *Stat. Sci.* **2020**, *35*, 579–592. [CrossRef]
33. Makridakis, S.; Spiliotis, E.; Assimakopoulos, V. The M4 Competition: 100,000 Time Series and 61 Forecasting Methods. *Int. J. Forecast.* **2020**, *36*, 54–74. [CrossRef]
34. Sbrana, G.; Silvestrini, A. Forecasting with the Damped Trend Model Using the Structural Approach. *Int. J. Prod. Econ.* **2020**, *226*, 107654. [CrossRef]
35. Baladram, S. *Extra Trees, Explained: A Visual Guide with Code Examples*; Medium: San Francisco, CA, USA, 2024.
36. Geurts, P.; Ernst, D.; Wehenkel, L. Extremely Randomized Trees. *Mach. Learn.* **2006**, *63*, 3–42. [CrossRef]
37. van den Briel, M.H.L.; Villalobos, J.R.; Hogg, G.L.; Lindemann, T.; Mulé, A.V. America West Airlines Develops Efficient Boarding Strategies. *Interfaces* **2005**, *35*, 191–201. [CrossRef]
38. Li, X.; de Groot, M.; Back, T. Using Forecasting to Evaluate the Impact of COVID-19 on Passenger Air Transport Demand 2021. *Decis. Sci.* **2023**, *54*, 394–409. [CrossRef] [PubMed]
39. Nyquist, D.C.; McFadden, K.L. A Study of the Airline Boarding Problem. *J. Air Transp. Manag.* **2008**, *14*, 197–204. [CrossRef]
40. Bachmat, E.; Berend, D.; Sapir, L.; Skiena, S.; Stolyarov, N. Analysis of Airplane Boarding via Space-Time Geometry and Random Matrix Theory. *J. Phys. A Math. Gen.* **2006**, *39*, L453–L459. [CrossRef]
41. Tanida, S.; Nishinari, K. Arranging the Order of Passengers on the Boarding Bridge to Reduce the Boarding Time for Single-Aisle Aircraft. *arXiv* **2021**, arXiv:2109.13431.
42. Schultz, M.; Soolaki, M.; Salari, M.; Bakhshian, E. A Combined Optimization-Simulation Approach for Modified Outside-in Boarding under COVID-19 Regulations Including Limited Baggage Compartment Capacities. *J. Air Transp. Manag.* **2023**, *106*, 102258. [CrossRef] [PubMed]
43. Fleurquin, P.; Ramasco, J.J.; Eguiluz, V.M. Systemic Delay Propagation in the US Airport Network. *Sci. Rep.* **2013**, *3*, 1159. [CrossRef] [PubMed]
44. Schultz, M.; Reitmann, S. Consideration of Passenger Interactions for the Prediction of Aircraft Boarding Time. *Aerospace* **2018**, *5*, 101. [CrossRef]
45. Tang, T.-Q.; Yang, S.-P.; Ou, H.; Chen, L.; Huang, H.-J. An Aircraft Boarding Model with the Group Behavior and the Quantity of Luggage. *Transp. Res. Part C Emerg. Technol.* **2018**, *93*, 115–127. [CrossRef]

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