Analysis of Dynamic Financial Performance of Airline Companies Using an Algorithm Combining Genetic Algorithm and DTW Clustering

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Abstract **– Air transport underpins modern mobility, trade and tourism making it a strategic pillar of the transport sector. Yet airlines often operate with fragile financial structures, underscoring the need for rigorous assessment of their financial performance. The literature features numerous studies that examine airlines' financial performances and conduct mutual comparisons by constructing single composite indices based on financial indicators. To the best of the knowledge, no previous study has examined similarity and outlier detection among airlines based on the temporal dynamics of their financial performance indicators, nor has it conducted a financial analysis of the passenger airlines in Serbia. To accomplish the first objective, using financial statement data including 27 indicators for 15 airlines operating in the country for the 2021–2024 period, the study introduces purpose-built algorithm for the time-series-clustering. The algorithm integrates DTW-based k-means clustering and a Genetic Algorithm, identifies the most discriminative indicators between airline groups and yields sharper inter-cluster separation, and thereby more reliable similarity and outlier analysis than classical time-series clustering methods.**

Addressing the second objective, the evidence indicates recovery from the COVID-19 crisis in Serbia's passenger air transport sector without sustained growth, calling for ongoing monitoring and targeted liquidity and resource allocation interventions.

Keywords **– Dynamic Time Warping, genetic algorithm, clustering, financial performance, outlier detection.**

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1. Introduction

Air transport is a crucial component of the transportation sector, as it ensures speed, reliability, and economic advantage [1]. According to the 2023 report of the International Air Transport Association (IATA), the airline industry in the Republic of Serbia employed approximately 6,200 people and generated around 0.2% of the country's total GDP. Moreover, the industry provides additional benefits through the expansion of supply chains, increased consumption, and tourism-related activity, which collectively contribute an estimated USD 1.3 billion and support around 45,500 jobs in Serbia [2]. However, companies operating within the airline industry often exhibit fragile financial structures [1], and the sector is highly sensitive to global economic conditions, largely depending on fuel prices, labor costs, and exchange rate fluctuations [3]. For instance, the COVID-19 pandemic had a devastating impact on the airline industry, leading to a sharp decline in air travel demand, mass grounding of fleets, significant revenue losses, and serious disruptions in the liquidity and profitability of most airlines worldwide [4]. The high vulnerability of the industry and ongoing uncertainty have intensified interest in examining the usage and behavior of traditional financial indicators, as well as analyses based on them, within the airline sector [5]. Financial performance analysis of airline companies allows for the identification of positive or negative aspects of business operations in comparison with competing firms, and for assessing the financial position of the entire sector.

This forms a foundation for making optimal decisions in enterprise management and the formulation of national regulatory policies [1].

In this research, a similarity analysis of 15 airlines that provide passenger air services in Republic of Serbia and had active status in 2025 was conducted, based on time series of financial performance indicators [6] to identify homogeneous groups of companies exhibiting similar performance change patterns in the period from 2021 to 2024, as well as isolating companies whose performance may be considered atypical relative to the rest of the sample.

In general, irrespective of the industry, there is no convergence within the academic and professional literature on the definition and evaluation of corporate financial performance [7], [8], [9]. It is broadly recommended to employ a wide range of indicators simultaneously for this purpose [10]. Financial performance of airlines has previously been evaluated using profitability, liquidity and solvency metrics [11]. In study [1], the usage of FAHP and GRA methods enabled the ranking of airlines' financial performance based on 12 financial-statement indicators, with criterion weights elicited from expert judgments. One study [12] has employed twelve financial indicators that describe airlines' profitability, operational performance, efficiency and liquidity, whereby harmonic indexes were constructed to enable the ranking of top 20 airlines woldwide. In another study, twelve financial ratios and TOPSIS were applied in order to derive a composite score for ranking the financial performance of four airlines over a six-year period [13].

Therefore, whereas prior studies primarily constructed single composite indices to compare and rank airlines and to track their performance over time, this study instead conducts a time-series clustering-based similarity analysis of the airlines, based on the dynamics of their financial indicators over the four-year period, using a purpose-built algorithm. In the study, the financial performance of passenger airlines is analyzed through comprehensive indicator sets grouped into three dimensions: (1) Financial return, comprising 10 indicators; (2) Liquidity and solvency, comprising 10 indicators; and (3) Asset turnover and resource utilization efficiency, comprising 7 indicators.

Time series clustering enables insight into dynamic patterns in corporate performance. To facilitate clearer and more robust differentiation of airlines according to temporal changes in their financial performance, a stochastic optimization algorithm was developed for time series clustering, which aims to increase the quality of clustering. This algorithm, referred to as GADTW, was applied independently to each of the three dimensions to identify dimension-specific clusters, and to the full indicator set to segment firms by overall financial performance.

GADTW conducts clustering using k-means clustering, where as the distance metric is used the Dynamic Time Warping (DTW), while the selection of parameters for clustering is achieved using a Genetic Algorithm (GA), which aims to improve clustering quality, measured by the Silhouette Score (SiS). Given that financial indicators for four companies were unavailable for 2024, while 11 companies had complete data for the 2021–2024 period, the DTW as a distance function for k-means clustering was applied. This method provides an optimal match between time series by stretching or compressing some segments of the series [14], can capture alternations between leading and lagging relationships of time series [15] and obtains the opportunity o cluster time series of unequal lengths.

Within GADTW, GA was used as a method for selecting indicators for clustering, whereby in each GA generation, for every subset of indicators selected by the GA, i.e., chromosome, the number of clusters that yields the highest Silhouette Score for that chromosome is identified. The maximum value of this score obtained for the optimal number of clusters for a given chromosome is used as the chromosome's fitness value, which serves to rank the entire population of chromosomes in the generation and form the next generation of chromosomes within GA. Finally, the clustering of companies within each dimension and on the set of all indicators is performed using the combination of chromosomes and number of clusters that in a given execution of GADTW generates the maximum value of SiS.

Accordingly, for each of the three financial performance dimensions, as well as for the entire set of indicators, GADTW performed clustering of companies based on the optimal combination of selected indicators and the number of clusters. This approach enables the maximization of inter-cluster differences while simultaneously enhancing intra-cluster homogeneity, allowing for clearer grouping of companies concerning their financial performance. Consequently, it also allows for more reliable identification of companies with anomalous temporal patterns in financial performance, i.e., those considered outliers, especially in cases where resulting outlying clusters include a significantly smaller number of instances relative to others and are spatially highly distant in the feature space from other clusters. In this way, the proposed algorithm can also be regarded as a method for unsupervised anomaly detection, whereby such methods do not use labelled datasets for training but independently identify patterns and deviations based on the intrinsic properties of the data. They operate under the assumption that abnormal data occur with significantly lower frequency compared to regular data within the available dataset.

Although various supervised and semi-supervised methods exist for anomaly detection, the task is generally treated as one of unsupervised learning, due to the inherently unlabeled nature of historical data and the unpredictable character of anomalies [16].

Furthermore, the algorithm pinpoints, per dimension and overall, the most discriminative indicators, i.e., those indicators that maximize between-cluster differences while preserving within-cluster homogeneity. These indicators thus hold high informational value for identifying outlying companies and segmenting firms by financial performance, and can thus be considered particularly important for financial analysis and risk assessment.

Additionally, the study includes a descriptive analysis of movements in key financial indicators, including trend analysis, for the group of companies from which those identified as atypical using the GADTW algorithm (across the three analyzed dimensions) were excluded for the period from 2021 to 2024. The exclusion of companies with atypical financial performance patterns, i.e., outliers, enables a more reliable insight into the overall condition of the airline industry through the analysis of a more stable and homogeneous sample. This, in turn, increased the reliability of generalized conclusions regarding the typical business performance and sectoral dynamics in the observed period.

2. K-means Clustering of Time Series Based on DTW

Time series clustering is the process of grouping time series concerning their similarity or characteristics, and it can be used in anomaly detection, classification, prediction and analysis of dynamic changes in the time series [17]. Due to its simplicity and flexibility, the most popular method in time series clustering is the k-means algorithm [18]. Various methods based on distance calculations are used for clustering time series data, including the Hausdorff distance [19], distances derived from Hidden Markov Models [20], Euclidean distance [21], and DTW. In time series clustering using the k-means algorithm, Euclidean distance has been shown to be the most efficient in terms of computational complexity, but demands compared time series be of the same length [17], [18], [22]. On another side, the DTW measure has been proven to be more accurate [22] and is increasingly used as a substitute for Euclidean distance in k-means due to its ability to flexibly align time series sequences [18]. Although it was initially used in the field of speech recognition [23], in the domain of data mining and information retrieval, DTW has been effectively utilized to automatically handle time distortions and varying temporal speeds in time-dependent data [24], as is can capture alternations between leading and lagging relationships of time series [15].

Using the Euclidean distance (ED), two time series X and Y, of length N, are compared using the formula:

$$ED(X,Y)=\sqrt{\sum_{t=1}^{N}(x_t-y_t)^2} \quad (1)$$

DTW is based on a similar idea to ED, but it applies local non-linear alignment. This is achieved by constructing a matrix M that calculates the ED between all pairs of points from time series X and Y. Based on this matrix, dynamic programming is used to compute the warping path, $w = \{w_1, w_2, ..., w_r\}$, in such a way that the following condition is met [25]:

$$DTW(X,Y)=\min\sqrt{\sum_{t=1}^{r}(w_i)} \quad (2)$$

In other words, DTW aligns time series by stretching or compressing segments of the series, enabling comparison of patterns that occur at different time points, i.e., evaluates the similarity of time series concerning their shapes [14]. The idea behind DTW-based K-means clustering lies in determining the optimal nonlinear mapping of the time axis of one of the series in order to minimize differences with another series. Specifically, DTW adjusts the temporal alignment of points in the first series such that the surface area between the resulting transformed series and the reference series is minimized and this surface is used as a quantitative measure of similarity between the two series [26].

Numerous studies have successfully integrated DTW into the analysis of financial time series [15], [27], [28], [29], [30]. For example, [31] used the DTW algorithm as a method for financial risk detection, applying it to financial data obtained through a sensor network.

3. Genetic Algorithms as a Feature Selection Method

Within the clustering framework, as a form of unsupervised learning, each cluster has maximum within-cluster similarity and minimum between-cluster similarity based on a certain similarity index. However, finding clusters in high-dimensional space is computationally demanding, may degrade the performance of the clustering and at the same time equally good candidate of features' subsets may produce different clusters [32]. Therefore, it is advisable to apply a dimensionality reduction technique before clustering, whereby reducing the number of irrelevant or redundant features drastically reduces the running time of a learning algorithm and obtains a more general concept of a real-world classification problem [33].

Within the dimensionality reduction framework, feature selection methods offer greater readability and interpretability, as they preserve the original feature representations, while feature extraction methods generate transformed variables that cannot be directly associated with the original features and have no physical meaning, whereby both approaches are capable of improving learning performance, lowering computational expenses and storage demands and building better generalizable models [32]. Feature selection (FS) is a process of selecting a subset of features from the original dataset during model construction, intending to optimize a specific criterion, and in general, includes four fundamental steps: candidate subset generation, subset evaluation, stopping criteria, and subset validation [33]. By eliminating redundant, less informative, or noisy features, FS can enhance the predictive power and interpretability of predictive models or classifiers [34]. A comprehensive review of feature-selection methods for clustering can be found in [35].

Feature selection methods are widely divided into four categories: filter, wrapper, hybrid and embedded methods, depending on the extent to which the selection technique is tied to the learning algorithm within the predictive model or classifier. Filter methods rely on intrinsic data properties to select features independently of the predictive model or classifier; they provide a feature weighting, ranking or subset as output [36], and their main advantage is their computational efficiency, since they operate independently of the learning algorithm. However, their drawback lies in typically inferior results when compared to other methods, as shown in [36], [37], [38].

Wrapper methods evaluate alternative feature subsets by guiding the search based on the results of the model that will use those features, which is, in the context of clustering, the clustering quality. In general, such methods: (1) Use heuristic strategies to search for relevant features, and (2) Evaluate clustering quality for each subset of features, iteratively repeating these two steps until a satisfactory clustering quality is achieved. Wrapper methods are generally more accurate than filter methods [36], [37], [38], [39], especially when the sample size is sufficiently large [40], but can be biased towards chosen classifier [32], computationally are more intensive than filter methods [32], [36], [39], and can be susceptible to the "nesting effect", which can lead to suboptimal results [38]. To alleviate the computational cost in the wrapper model, in hybrid models, filtering statistical criteria is primarily applied to select the candidate feature subsets, whereby, later, the subset with the highest classification accuracy is chosen [41].

In the case of the embedded method, FS is strongly coupled with the classifier itself [40], and model fitting and feature selection are performed simultaneously.

Such methods utilize internal model information to guide feature selection, aiming to strike a balance between model performance and computational cost [42].

Genetic Algorithms (GA) can evolve new features based on selected ones and expand the search space to discover better solutions for feature selection [43]. As demonstrated in the studies by [44], and [45], GA represent an adaptive and effective wrapper method for feature selection, particularly useful in situations where the search space is not mathematically characterized, not fully understood, or is highly dimensional [40]. GA are heuristic techniques inspired by the process of natural evolution in human development [46], and involve iterative procedures that manipulate a population of chromosomes (potential solutions) to generate a new population through genetic operators such as crossover and mutation. Five key components of GA include: chromosome encoding, fitness evaluation, selection mechanisms, genetic operators, and stopping criteria [47]. The performance of a GA depends on several factors, including the chosen crossover and mutation strategies, the fitness function, population size, and the probabilities assigned to genetic operations [43].

A survey of existing GA based clustering algorithms and their applications across multiple problems and domains is presented in [48]. Reference [49] analyzed the effectiveness of GAs in feature selection using multiple clustering quality evaluation metrics and various clustering algorithms and have shown that GA significantly enhanced clustering performance across all algorithms examined in terms of SiS. The efficiency of GA as an FS method for clustering has also been confirmed by [50].

4. Research Methodology

According to records from the Serbian Business Registers Agency, 57 companies engaged in passenger air transport and classified under activity code 5110 held active status in 2025. The research sample was drawn by randomly selecting 20 passenger airlines from this population, retaining 15 in the final sample that had complete financial statements for 2021–2023.

The research focuses on three dimensions of financial performance of airline companies, whereby the first dimension (D_1) - financial return, refers to a company's ability to efficiently generate profit and manage productivity, the second dimension (D_2) - liquidity and solvency, includes indicators that assess a company's ability to meet its short-term obligations, as well as its financial sustainability and the third dimension (D_3) - asset turnover and resource utilization efficiency, measures how successfully a company utilizes its resources to generate revenue and maintain operational liquidity.

Table 1 includes the sets of indicators used to evaluate the performance of passenger airlines from the sample within each performance dimension.

Table 1. Indicators within financial dimensions and their labels

D_1	D_2	D_3
Net Profit Margin (NPM)	Current Ratio (CuR)	Days Sales Outstanding (DSO)
Gross Profit Margin (GPM)	Quick Ratio (QR)	Days Inventory Outstanding (DIO)
Operating Profit Rate (OPR)	Cash Ratio (CaR)	Days Payables Outstanding (DPO)
Operating Result Before Depreciation (EBITDA)	Net Working Capital (NWC)	Cash Conversion Cycle (CCC)
EBITDA Margin (EM)	Total Financial Liabilities (TFL)	Fixed Asset Turnover (FAT)
Return on Assets (ROA)	Debt-to-Equity Ratio (D/E)	Capital Turnover (CAT)
Return on Equity (ROE)	Fixed Assets to Capital Employed Ratio (FA/CE)	Total Asset Turnover (TAT)
Average Annual Gross Cost per Employee (AGCE)	Fixed Assets to Long-Term Financing Ratio (FA/LTF)	
Average Monthly Gross Cost per Employee (MGCE)	Fixed Assets to Total Liabilities and Equity Ratio (FA/TLE)	
Average Revenue per Employee (RE)	Debt Repayment Period (DRP)	

Given that financial and operational indicators for the year 2024 were unavailable for four of the 15 airline companies, and given the proven efficiency of the DTW method in time series clustering, which was discussed previously in the paper, time series clustering using the DTW method was applied for analyzing company similarities, as previously explained. For each analyzed dimension of financial performance, time series clustering was performed using the TimeSeriesKMeans algorithm from the tslearn Python library [51], where DTW distance was used as the metric function, with the default DTW configuration and a fixed random seed. The GA component of the algorithm was implemented in a procedural style, without defining specific classes for populations, individuals, or operators, nor relying on specialized libraries.

This provided full control over chromosome structure, selection of crossover and mutation operators, and population selection and evaluation procedures, which was necessary to fully adapt the algorithm to the objective of optimizing time series clustering. GADTW uses the Silhouette Score [52] as its objective function. This metric captures within-cluster cohesion, i.e. how similar an object is to its own cluster compared to other clusters (between-cluster separation) and ranges from -1 to +1, enabling intuitive interpretation of results, whereby a higher value indicates better clustering quality. Within GADTW, SiS is implemented using the silhouette_score() function from the scikit-learn Python library [53] and uses the Euclidean distance as a distance indicator.

The analysis was conducted independently for each of the three financial performance dimensions (denoted as D_1, D_2, D_3), where D_1 and D_2 each contained 10 indicators ($|I_1| = |I_2| = 10$), and D_3 contained 7 indicators ($|I_3| = 7$), with I_k representing the set of all indicators for dimension D_k. For each of the 15 observed companies C_j ($j = 1,\ldots,15$) and each dimension D_k, a two-dimensional matrix $X_{kj} \in \mathbb{R}^{n_k} \times T_j$ was formed, where n_k is the number of indicators in dimension D_k and T_j is the number of time points for company j ($T_j = 3$ for the four companies lacking 2024 data; $T_j = 4$ for the remaining 11 companies).

Before clustering, data preparation included normalization and transformation. Each matrix X_{kj} was standardized across indicators using Z-score normalization. Then, each normalized matrix X_{kj} was transformed into a vector x_{kj} by ordering all indicator values sequentially along the time dimension. Thus, each company was represented as a one-dimensional time series reflecting the simultaneous dynamics of multiple indicators over time. This transformation was applied regardless of the use of the genetic algorithm and was also performed in cases where the full set of indicators was used without feature selection. It was necessary since the DTW metric requires univariate time series input.

The steps of the GADTW algorithm, for each financial performance dimension D_k, generally include:

1) **Population initialization**: Generation of 20 random subsets of indicators (chromosomes), i.e., subsets $h \subseteq I_k$, with random lengths ranging from 2 to n_k genes. The minimum of 2 genes is determined by technical requirements for the crossover operation within the GA. Each chromosome represents an individual in the population, i.e., a subset of financial indicators used as input parameters in the clustering of companies for the given dimension D_k.

2) **Fitness function evaluation**: For each chromosome h and each number of clusters $k \in [2, 9]$, clustering is performed using the time series k-means algorithm with DTW as the distance metric. The fitness value of the chromosome is taken as the maximum Silhouette Score (SiS) obtained for the optimal number of clusters for that chromosome.
3) **Selection and crossover**: The five highest-ranked chromosomes based on the SiS are retained in the next generation, while the remaining individuals are generated through crossover, by combining parental chromosomes and mutation, where one gene (indicator) in a chromosome is replaced by another from the set I_k.
4) **Evolution through generations**: The algorithm is executed iteratively over 10 generations. Each new population is formed based on previously selected and recombined individuals, and all new individuals in each generation are evaluated.
5) **Identification of the optimal solution**: The best global solution is defined as the chromosome which, in combination with its optimal number of clusters, achieved the highest SiS value during the entire process. GADTW uses an explicit memory mechanism that stores the globally best solution found so far during each evolution cycle, ensuring the robustness of the algorithm and the stability of the final clustering results. This guarantees that the optimal solution, defined as the combination of indicator subset and cluster number with the highest Silhouette coefficient, is not lost due to potential population degradation in later generations, despite the stochastic nature of selection, crossover, and mutation.
6) **Reproducibility**: Due to multiple elements of randomness in the GA component, including random population initialization, parent selection for crossover, crossover points during recombination, mutation probability, and indicator selection for filling under-length chromosomes, GADTW was executed 10 times for each dimension. The final clustering solution for each dimension and chromosome size threshold was chosen as the one with the highest SiS value among these 10 iterations. Testing of the GADTW algorithm on the available dataset showed that the highest SiS values were repeatedly obtained across multiple runs, suggesting that the selected solutions are optimal or near optimal.

The general model of the GADTW algorithm is illustrated in Figure 1.

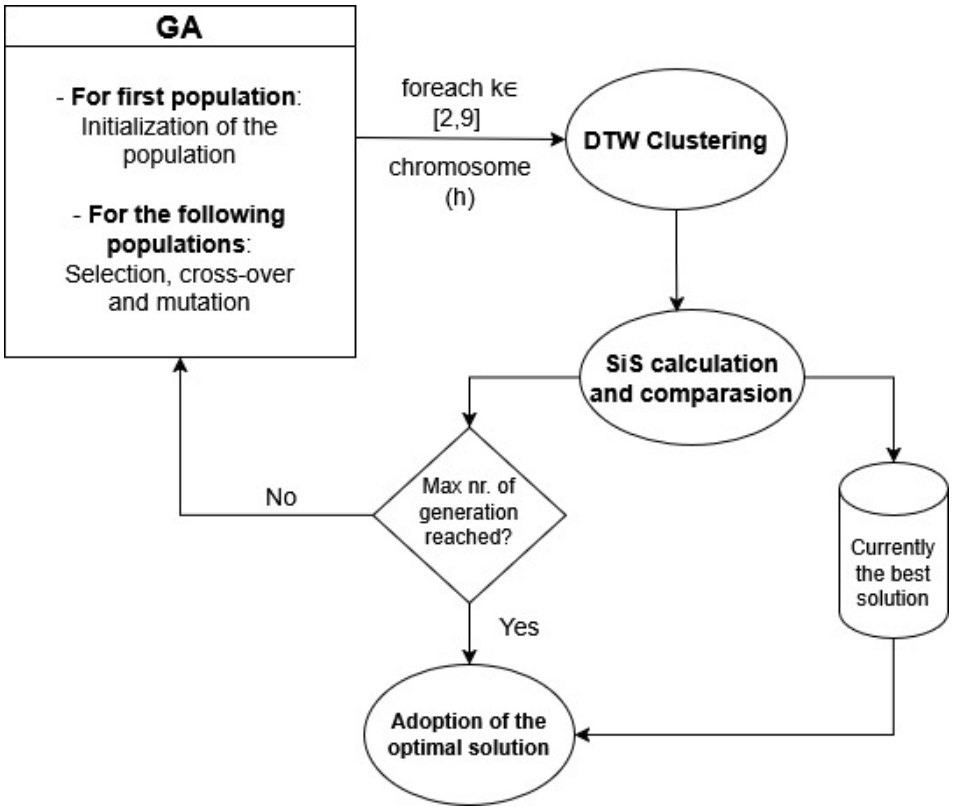


Figure 1. Abstract presentation of the GADTW algorithm

The population size and number of generations in GA were defined based on empirical testing of the GA application, which demonstrated that increasing these thresholds, although increasing computational complexity and runtime, did not significantly improve clustering quality as measured by the SiS.

During population evolution, the crossover and mutation operators played a key role in generating diverse individuals. Crossover was performed using the simple one-point crossover method, in which two parent chromosomes were randomly split at a given point and then recombined into a new offspring. This allowed mixing of different parts of genetic information, i.e., indicators, from both parents. Mutation was applied with a 30% probability, meaning that on average every third offspring underwent a modification of its genetic structure, i.e., its selected indicator set. The purpose of this operation was not to improve the immediate clustering quality but to maintain genetic diversity in the population and prevent the algorithm from converging toward a local optimum, i.e., a suboptimal solution that may arise if all individuals become too similar over generations.

To assess the effects of GADTW algorithm, for each dimension D_k a reference variant of the algorithm was constructed (referred to as the DTW-R), excluding the GA component, which performed clustering on the full set of indicators I_k for the given dimension , optimizing only the number of clusters ($k \in [2, 9]$) using the SiS as the objective function. The DTW-R was configured to perform clustering on the full set of indicators used in this study, as well, and its results were compared with those of GADTW, which used the full set of 27 indicators. DTW-R algorithm contained no stochastic elements and did not require repeated executions to identify the best solution. Through a comparison of GADTW and DTW-R, covering obtained SiS values, the number of clusters, cluster memberships, and 2D maps of the resulting clusters, it is evaluated how indicator selection, i.e., GA component of the GADTW, affects clustering outcomes. In this way the hypothesis was tested that GADTW yields more homogeneous within-cluster structure, greater between-cluster separation, and clearer identification of outlier airlines than DTW-R.

To complement the foregoing comparative analysis of algorithms and facilitate a qualitative appraisal of similarity in passenger airlines' financial performance dynamics, transformed vectors x_k were used for the graphical presentation of clustering results in 2D space using Principal Component Analysis (PCA), which was implemented using the PCA class from the sklearn.decomposition module [53]. The main idea of PCA is to reduce the dimensionality of a data set, while retaining as much as possible of the variation present in the data set, by transforming it to the principal components, which are uncorrelated, and which are ordered so that the first few retain most of the variation present in the data set [54].

PCA was implemented to extract the two main components, which made it possible to construct a 2D scatter diagram, whereby plt.scatter() function from the matplotlib.pyplot library [55] was used, and companies are shown as points in the plane determined by the first and second PCA components, with each point additionally labelled based on their membership in the formed clusters.

To further illuminate differences in financial performance and their temporal dynamics among the groups obtained by GADTW, by performance dimension and overall, an analysis of average Z-scores for the indicators selected by GADTW as optimal for clustering was conducted.

Additionally, with the aim of gaining insight into the financial condition of the passenger air transport sector in Serbia, a descriptive analysis of trends in key financial indicators was conducted, including trend analysis for each indicator and for the set of companies from which those identified as atypical by the GADTW algorithm (within the three analyzed dimensions) were excluded for the period 2021–2024. The initial group included 11 companies with available data for the full period. To identify trends in the behavior of key financial indicators, simple linear regression was applied to each indicator. The years within the observed period were treated as independent variables, while the average annual values for each indicator were treated as the dependent variable. Based on the slope coefficient and p-value, the statistical significance and direction of the trend were estimated, where negative coefficients indicated declining, and positive coefficients indicated increasing trends over the observed time interval. The use of more complex trend analysis models was not justified due to the limited timeframe covered by the study. For this trend analysis, the function linregress() from the scipy.stats Python library was used.

5. Research Results

In this section, the empirical results of the study are presented. First, GADTW and DTW-R are compared in terms of clustering quality as measured by the SiS, cluster counts and memberships, and 2D PCA visualizations of clusters. Next, the indicators with the greatest discriminative power across airline groups, as identified by GADTW, are determined, and cluster-level average z-scores for these indicators are reported. This analysis is conducted in the first three subsections at the level of each financial performance dimension, and in the fourth subsection for the full indicator set, i.e., overall financial performance of the passenger airlines. The fifth subsection reports the results of descriptive analysis of financial indicators, at the sample level, including trend analysis, by performance dimension, for the period 2021–2024.

5.1. Analysis of Company Clusters Based on the Financial Return Dimension

When GADTW was applied to the set of time series within the financial return dimension, the highest obtained Silhouette Score (SiS) was 0.743, indicating significantly higher clustering quality compared to the case in which the DTW-R algorithm was applied, where the SiS reached only 0.159.

Figure 2 presents the airline company clusters obtained through both the GADTW (a) and DTW-R (b), represented in a two-dimensional Principal Component Analysis (PCA) space for the financial return dimension.

In the configuration with the highest SiS score, GADTW grouped 13 companies into Cluster 0, while Cluster 1 consisted of two companies for which data were available for the entire period from 2021 to 2024. The indicators selected by GADTW for clustering, corresponding to the highest achieved SiS, were Net Profit Margin (NPM) and Return on Assets (ROA), indicating that the two atypical companies in the smaller cluster differed most significantly from the others in the sample in terms of the time series behavior of these two indicators during the analyzed period. On the other hand, as shown in Figure 2 (b), the DTW-R algorithm identified three clusters. Two of them included six companies each, while the third cluster contained three companies, among which two were also identified by GADTW as outliers. These two companies are highlighted in the diagram with red circles.

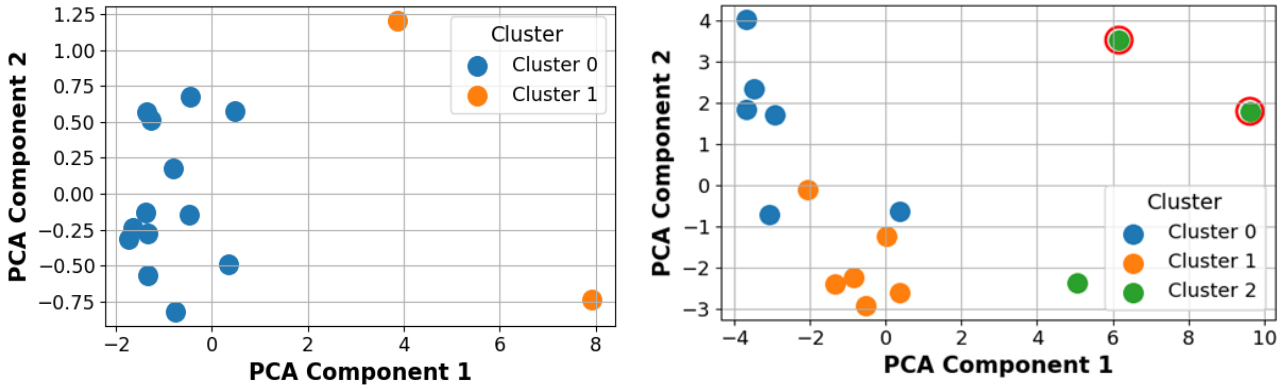


Figure 2. Cluster representation for D_1 in PCA space, obtained by a) GADTW and b) DTW-R

As illustrated in Figure 3, the 13 companies in Cluster 0, denoted in black, exhibited below-average values for the two relevant indicators and had distinct trends in the movement of their average normalized values compared to the two companies in Cluster 1, denoted in gray. In contrast, Cluster 1, which contained only two companies, showed profitability indicator values significantly above the average, indicating that these were indeed atypical companies in terms of the financial return dimension.

A review of the remaining indicators within this dimension, which were not used as the basis for clustering, revealed that two firms in Cluster 0 had unusually low or even zero cost bases per employee. Specifically, the first company had no registered employees during the entire observation period, while the second company had no registered employees after 2021. Such findings may point to accounting irregularities or manipulations, or possibly to a fully outsourced workforce in these companies, thus confirming that their classification as atypical was justified.

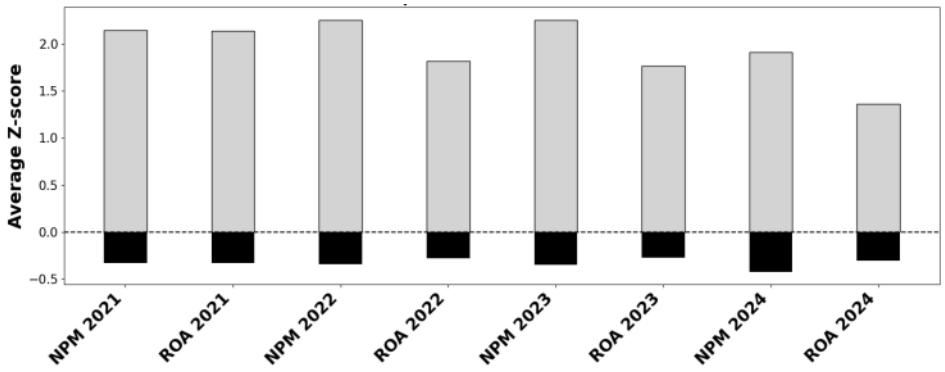
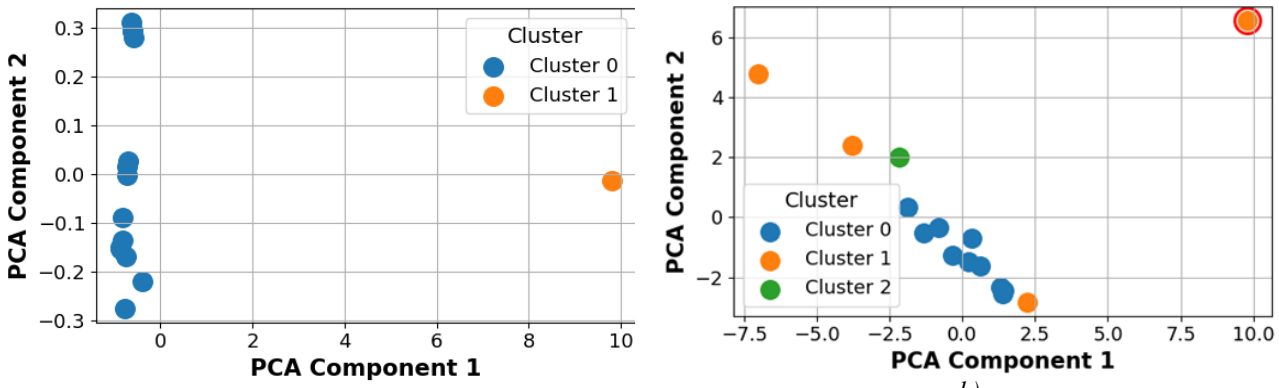


Figure 3. Comparison of clusters based on GADTW-selected indicators for D_1 (black = cluster 0, gray = cluster 1)

5.2. Analysis of Company Clusters Based on the Liquidity and Solvency Dimension

Within the 10 iterations of the GADTW algorithm to the liquidity and solvency dimension, the highest achieved SiS was 0.903. For this instance of the model, two clusters were identified, as shown in Figure 4 (a).

Cluster 0 of this DTW model instance included 14 airlines, while Cluster 1 comprised only a single company. This particular company was one of the two firms previously identified as atypical by the GADTW clustering under the financial return dimension. The indicators that proved to be most discriminative in forming clusters through GADTW were: Current Ratio (CuR) and Quick Ratio (QR).



a) *b)*

Figure 4. Clusters for D_2 in PCA space, obtained by a) GADTW and b) DTW-R

In contrast, the DTW-R algorithm achieved a SiS value of 0.278 and identified three clusters: Cluster 0 comprised 10 companies, Cluster 1 included four companies, and Cluster 2 consisted of a single company, namely Air Serbia. In this segmentation, the company identified as atypical by GADTW (marked with red circle) was grouped with three other companies within Cluster 1 by DTW-R and was spatially separated in the 2D PCA space from the rest of the sample, as shown in Figure 4 (b).

As illustrated in Figure 5, the company in Cluster 1 exhibited extremely high values of the QR and CuR indicators throughout the observed period, relative to the average normalized Z-score values of the companies in Cluster 0. This suggests that the company had a significant surplus of current assets relative to its short-term liabilities, pointing not only to strong liquidity but also to a fundamentally different business model compared to other companies in the sample, as well as to potential irregularities discussed in the previous section

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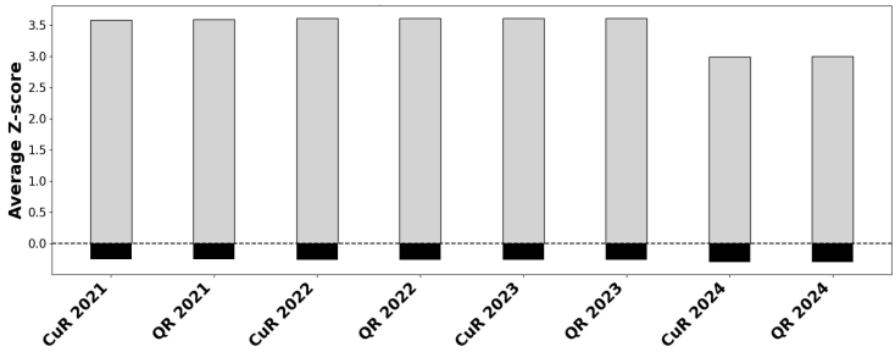
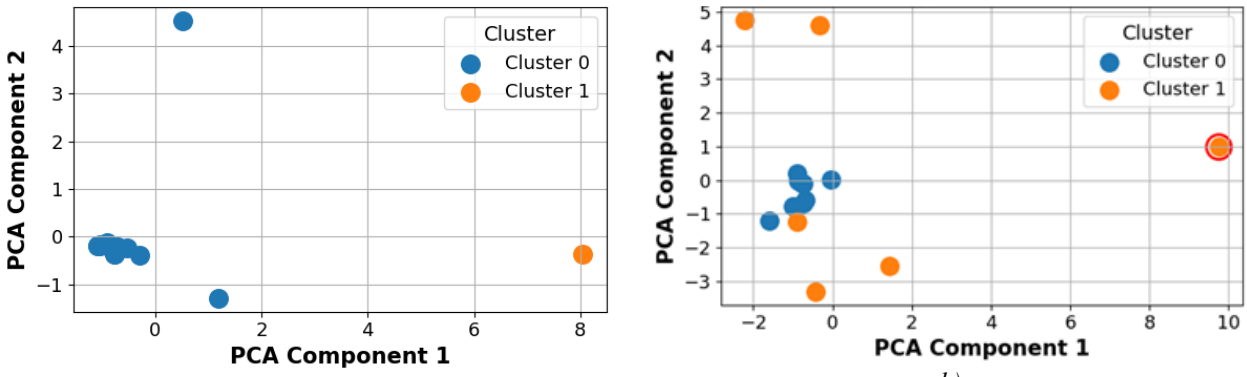


Figure 5. Comparison of clusters based on GADTW-selected indicators for D_2 (black = Cluster 0, gray = Cluster 1)

5.3. Analysis of Company Clusters Based on the Asset Turnover and Resource Utilization Efficiency Dimension

The instance of the GADTW algorithm that achieved the highest SiS of 0.772 identified two company clusters: Cluster 0, which included 14 companies, and Cluster 1, which contained a single company. This company had not been previously identified as atypical in either of the two preceding financial performance dimensions.

The indicators that enabled this segmentation were the Cash Conversion Cycle (CCC) and Days Payables Outstanding (DPO). In this case, the DTW-R algorithm also identified two clusters, but with a considerably lower SiS value of 0.240. The smaller cluster comprised six companies, including the one identified by GADTW. This company was also the most spatially distant from other companies within its cluster in the PCA space, as shown in Figure 6, where it is highlighted with a red circle.



a) *b)*

Figure 6. Clusters for D_3 in PCA space, obtained by a) GADTW and b) DTW-R

As shown in Figure 7, the outlier identified by GADTW exhibited significantly higher values for both CCC and DPO indicators throughout the observed period, particularly in 2022 and 2023, compared to the rest of the sample.

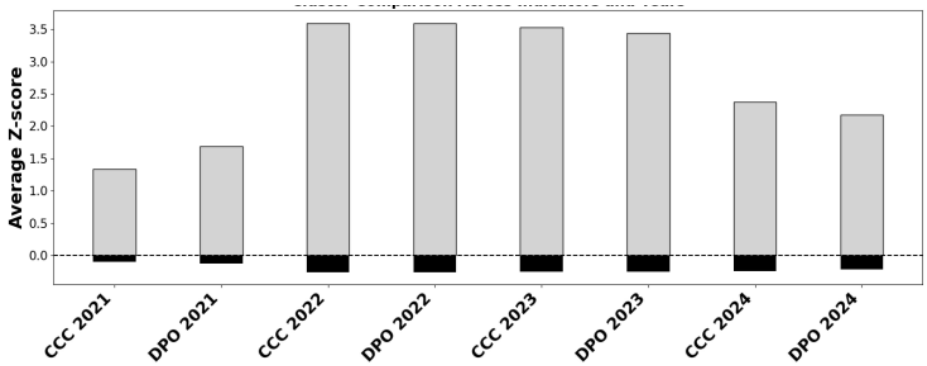


Figure 7. Comparison of clusters based on GADTW-selected indicators for D_3 (black = Cluster 0, gray = Cluster 1)

Unlike companies identified as atypical in the previous two dimensions, where extreme values of positively interpreted indicators suggested strong financial performance, in this case, the outlier company showed extreme values for indicators whose higher levels indicate negative aspects of operational performance. Extremely high DPO and CCC values suggest that this airline significantly delays the settlement of its obligations while simultaneously failing to convert inventory and receivables into cash efficiently. Such imbalances point to structural inefficiencies in working capital management and indicate liquidity risk, which, over the long term, could undermine the company's financial sustainability and reputation, potentially leading to bankruptcy.

5.4. Analysis of Company Clusters Based on the Full Set of Financial Indicators

The highest SiS obtained across 10 iterations of the GADTW algorithm applied to the full set of indicators describing corporate financial performance was 0.733.

In this instance, the algorithm identified two company clusters, with Cluster 1 containing a single company. As illustrated in Figure 8, this company was previously identified as an outlier in the GADTW clustering of both the financial return and liquidity and solvency dimensions. To enable comparative analysis with the GADTW results for individual dimensions, the three companies identified as outliers in the dimension-specific analyses are marked with an "x" in Figure 8 (a). The companies detected in the first and second dimensions appear more clearly separated in the 2D PCA space compared to the company identified solely within the third dimension. The clustering for the full set of 27 indicators was based on five selected indicators: NPM, OPR, EBITDA, QR, and CuR. Notably, none of the selected indicators originated from the asset turnover and resource utilization efficiency dimension.

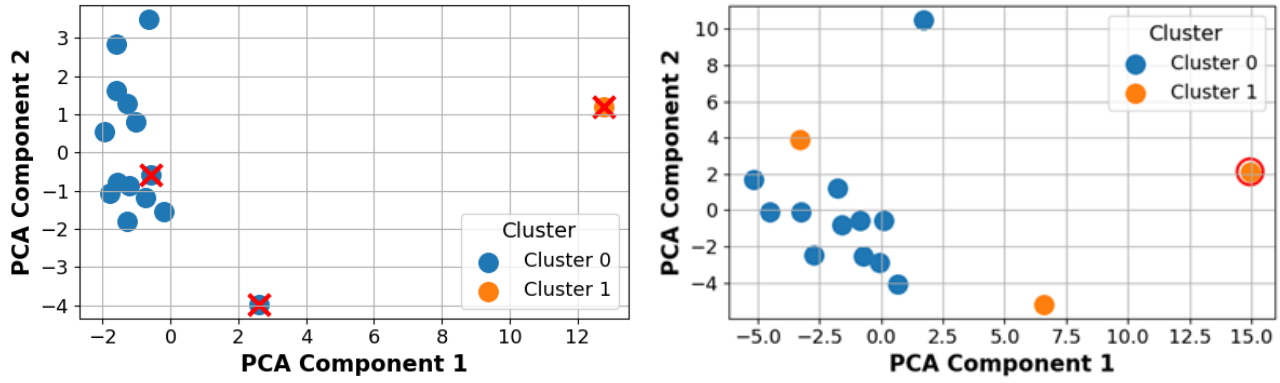


Figure 8. Representation of clusters for the full set of financial performance indicators, obtained by a) GADTW and b) DTW-R

In contrast, the DTW-R algorithm, which clustered time series based on all 27 indicators, yielded a SiS value of 0.189. It identified two clusters, with the smaller Cluster 1 containing three companies, as shown in Figure 8 (b). Among them was the company identified by GADTW across the full set of indicators and in the first two dimensions. This company, as in the previous cases, was spatially isolated from the rest of the sample in the PCA space, as depicted in Figure 8. The smaller DTW-R cluster also included the second company previously identified by GADTW within the financial return dimension.

5.5. Descriptive Analysis of Financial Indicators

Table 2 presents the average values of financial indicators within the financial return dimension for 9 companies over the period 2021–2024. From the initial set of 11 companies with complete data for this period, 2 companies identified as outliers by the GADTW algorithm within this dimension were excluded.

Table 2. Average values of indicators within the financial return dimension for 9 companies, 2021–2024

FI	2021	2022	2023	2024	slope	R^2	p
GPM	0.396	0.390	0.371	0.354	-0.014	0.962	0.019
NPM	0.090	0.122	0.088	0.081	-0.006	0.186	0.568
OPR	0.110	0.130	0.097	0.102	-0.006	0.246	0.504
ROA	0.190	0.312	0.227	0.121	-0.029	0.224	0.526
ROE	0.823	1.578	0.335	0.268	-0.291	0.386	0.379
EBITDA	718,970,37	1,050,223,000	1,316,176,87	1,746,168,75	334,754,900.00	0.991	0.004
EM	0.257	0.230	0.207	0.203	-0.018	0.923	0.039
AGCE	1,794,787.62	2,244,077.87	2,537,974.25	2,876,306.375	353,845.262	0.992	0.004
MGCE	149,565.62	187,006.5	211,497.875	239,692.125	29,487.087	0.992	0.004
RE	8,510,305,324	13,872,117,921	15,717,669,260.125	25,390,095,624.625	5,248,492,224.01	0.926	0.038

The GPM exhibited a mild but statistically significant decline during the observed period, from 0.396 in 2021 to 0.354 in 2024 ($R^2 = 0.947$; $p = 0.027$), indicating a reduction in the operational gross profit generation capacity of the analyzed companies. A statistically significant decline was also observed in the EBITDA Margin ($p = 0.039$), while decreases in NPM, ROA, ROE, and OPR were also recorded; however, these declines were not statistically significant. Conversely, a statistically significant upward trend was present in the EBITDA ($R^2 = 0.991$; $p = 0.004$), AGCE ($R^2 = 0.992$; $p = 0.004$), MGCE ($R^2 = 0.992$; $p = 0.004$), and RE ($R^2 = 0.926$; $p = 0.038$). Overall, the increase in EBITDA suggests business expansion and potential productivity improvements.

However, the decline in most relative profitability indicators implies that higher revenues and EBITDA have not resulted in proportionally improved profitability, with rising labor costs likely being a contributing factor to the erosion of profit margins. These findings suggest that, despite expanding business volume, airlines in the observed period faced diminished relative profitability.

Table 3, displays the yearly average values of financial indicators within the liquidity and solvency dimension for 10 companies from 2021 to 2024, with one company, identified as an outlier by the GADTW algorithm, excluded from the initial set of 11.

Table 3. Average values of indicators within the liquidity and solvency dimension for 10 companies, 2021–2024

FI	2021	2022	2023	2024	slope	R^2	p
CuR	2.76	1.38	1.05	1.22	-0.49	0.66	0.19
QR	2.65	1.31	0.79	0.89	-0.58	0.76	0.13
CaR	2.29	1.06	0.48	0.51	-0.59	0.81	0.10
NWC	721,415,181.82	640,788,545.45	466,034,454.55	337,891,181.8	-132,532,609.09	0.98	0.01
TFL	878,715,727.27	1,022,340,909.09	974,473,727.27	1,536,178,727.27	192,452,181.82	0.71	0.158
D/E	13.64	4.97	3.18	2.20	-3.61	0.80	0.11
FA/CE	12.15	2.43	2.25	1.80	-3.12	0.65	0.19
FA/LTF	0.69	0.56	0.80	0.89	0.09	0.59	0.23
FA/TLE	0.30	0.26	0.31	0.34	0.02	0.51	0.29
DRP	0.77	0.69	0.52	0.61	-0.06	0.61	0.22

Liquidity indicators such as CuR, QR, and CaR show a decreasing trend from 2021 to 2023, followed by a slight recovery in 2024, though average values remained significantly below their 2021 levels. The Net Working Capital (NWC) exhibited a marked and statistically significant decline ($R^2 = 0.98$; $p = 0.01$), dropping from RSD 721 million in 2021 to RSD 337 million in 2024, with a pronounced annual slope of RSD 132 million.

This reduction in working capital and liquidity may threaten companies' operational flexibility and their ability to sustain uninterrupted operations without additional funding sources. Regarding Total Financial Liabilities (TFL), the indicator decreased in 2023 but showed a dramatic increase in 2024, suggesting heightened indebtedness. However, over the full period, this growth was not statistically significant ($p = 0.16$).

Conversely, the Debt-to-Equity Ratio (D/E) fell significantly from 13.64 in 2021 to 2.20 in 2024, indicating a relative improvement in capital structure. Still, this decrease was not statistically significant at the 95% confidence level ($p = 0.11$). The decline in D/E alongside increased liabilities, particularly in 2024, can be interpreted as the result of intensive recapitalization efforts during 2021–2024. The average equity value of the 10 companies rose from RSD 75 million in 2021 to RSD 1.25 billion in 2024. Notably, in 2021, four companies, including Air Serbia and Wizz Air, reported a book value of equity equal to zero. The FA/CE and FA/LTF ratios also indicate a decline in the share of fixed assets relative to capital and long-term sources, respectively, reinforcing the conclusion of broad recapitalization. Meanwhile, FA/TLE and DRP showed only minor changes, with a slight increase in FA/TLE and a slight decrease in DRP, neither of which was statistically significant. Based on these findings, it can be concluded that the analyzed airline companies underwent profound changes in their balance sheet structure during the observed period, driven by the need to maintain solvency and mitigate the effects of the COVID-19 crisis. Recapitalization, as the central mechanism of financial recovery, allowed companies to reduce the relative debt burden and create financial room for future investment and stabilization of operational flows.

However, weakened liquidity relative to 2021 and the continued decline of net working capital, despite substantial recapitalization, represent key warning signs requiring additional attention from both management and regulatory authorities.

Regarding the asset turnover and resource utilization efficiency dimension, the average values for 10 companies (with one outlier identified by GADTW excluded) from 2021 to 2024 indicate considerable volatility across all indicators. This reflects ongoing uncertainty and shifts in the post-COVID business environment. As shown in Table 4, extreme DPO and CCC values in 2021 suggest extraordinary conditions in payables and working capital management, where companies employed defensive financial strategies, extending payment terms to suppliers and experiencing slowed capital turnover. These values fluctuated in the following years without a consistent trend. The highest R^2 value was recorded for the Days Sales Outstanding (DSO) indicator ($R^2 = 0.82$), indicating a strong upward trend in accounts receivable collection periods, which could jeopardize liquidity. Still, the trend was not statistically significant ($p = 0.10$). Meanwhile, the Days Inventory Outstanding (DIO) showed signs of recovery after peaking in 2021 due to reduced traffic volume and inventory accumulation during the pandemic, but remained unstable throughout the later years.

Table 4. Average values of indicators within the asset turnover and resource utilization efficiency dimension for 10 companies, 2021–2024

FI	2021	2022	2023	2024	slope	R^2	p
DPO	5936.84	446.89	2123.49	3580.37	-539.28	0.09	0.70
DSO	55.89	62.88	97.40	204.76	48.11	0.82	0.10
DIO	1840.08	98.72	300.62	179.90	-477.86	0.56	0.25
CAT	4.39	7.44	5.04	3.51	-0.50	0.15	0.61
FAT	196.46	320.23	3.59	51.09	-75.28	0.46	0.32
TAT	2.61	4.00	4.05	4.4	0.54	0.78	0.11
CCC	7776.82	545.55	2424.12	3760.27	-1017.11	0.18	0.57

The Total Asset Turnover (TAT), an indicator of asset utilization efficiency, showed consistent growth during the observed period, with a high coefficient of determination ($R^2 = 0.78$), indicating a positive trend in revenue generation per unit of assets. This suggests that airline companies began revitalizing their business capacities post-COVID and implemented more rational resource management, improving operational efficiency. However, this growth was not statistically significant ($p = 0.11$).

Still, the decline in average values of Fixed Asset Turnover (FAT) and Capital Turnover (CAT) over the last two years may reflect capital investments and capacity expansion that have not yet translated into proportional revenue growth. These findings indicate that, while some companies are recovering successfully, the overall industry continues to exhibit signs of post-pandemic instability in resource utilisation efficiency and working capital management.

6. Conclusion

Clustering of time series data on financial indicators, using a sample of airline companies, proved to be a valuable method for segmenting firms based on multi-year patterns in their financial performance, allowing for more in-depth insights than static analyses. By applying DTW-based clustering, greater flexibility was achieved in comparing series of varying lengths and dynamics, enabling the identification of structural similarities that traditional metrics would not capture.

A comparative analysis of the GADTW and DTW-R algorithms demonstrated that the DTW method, without prior dimensionality reduction of the indicator set via a genetic algorithm (GA), but only optimizing the number of clusters, showed adequate robustness in grouping companies with similar financial performance, thus validating its effectiveness in financial analysis. However, compared to the more rigorous GADTW algorithm, which includes a GA-based feature selection component, the DTW-R algorithm exhibited limited ability to detect companies with significantly different temporal dynamics in financial indicators. Identifying such outliers required additional projection into the PCA space to visualize their spatial dislocation from the rest of the sample. In contrast, the GADTW algorithm did not require further analysis of firm distribution in PCA space and additionally enabled the automatic identification of those financial indicators with the highest discriminative power between typical and atypical firms, thus allowing for a deeper and more targeted understanding of the drivers behind the identified outliers. As such, the GADTW algorithm offers added value to analysts and decision makers seeking effective tools for detecting business-specific features, financial risks, or potential strategic anomalies in the domain of financial management.

Based on a comprehensive descriptive analysis of the three key dimensions of financial performance – profitability, liquidity and solvency, and resource utilization efficiency, it can be concluded that the analyzed sector was undergoing a period of intensive post-pandemic restructuring during 2021–2024. This phase was marked by simultaneous signs of recovery and numerous challenges. In the area of profitability, despite an increase in total revenue, EBITDA, and overall business volume, a decline was observed in nearly all relative profitability indicators, indicating that growth in operations did not translate into proportional improvements in profitability. This trend was likely driven by rising costs, such as those related to labor and fuel procurement, suggesting reduced operational efficiency per unit of revenue.

In the domain of liquidity and solvency, the data reveal a concerning decline in working capital, rising indebtedness, and deterioration in key liquidity indicators, despite noticeable strengthening of the equity base through recapitalization. These developments indicate that companies used recapitalization to repair their balance sheets, but significant risks in the domain of solvency remain, which may limit the operational flexibility of these firms. Concerning asset management and working capital turnover, findings point to high volatility in indicators throughout the observed period, with occasional signs of recovery through improved asset efficiency, but also a worrying trend of lengthening accounts receivable collection periods, which could further threaten liquidity.

Overall, the results of the descriptive analysis indicate that the commercial air transport sector was recovering from the 2020–2021 crisis during the analyzed period but had yet to establish sustainable patterns of growth and efficiency in many areas. Accordingly, continued monitoring of financial performance and a focused effort on optimizing resources and liquidity remain crucial for enhancing the competitiveness, resilience, and financial sustainability of companies within this sector.

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