A Statistical Review of European Carriers' Flight Delays and the Assessment of Delay Factors

Analisis Statistik dan Tinjauan Literatur Terkait Faktor Keterlambatan Penerbangan

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Abstract

Disruption is an inherent risk that might arise because of the complexity and dynamic nature of air transport operations. In the aviation business, disruption can happen for a variety of reasons, including poor weather, strikes, and political factors. This study aims to analyse flight delays that European airlines encounter and assess the dependencies between different operation parameters through correspondence analysis in contingency tables that are visually represented using correspondence maps. This study examined data from selected European airlines between 2018 and 2022, which contained information on the length of delay, the reasons associated with it, and the specific characteristics of each flight, such as the type of flight, the type of aircraft, and the scheduled departure time. The result showed that even though there was a large decrease in the overall number of flights operated during the pandemic period in 2020 and 2021, the percentage of delayed flights still varies above 55%. Long-haul flights and larger aircraft tend to have longer delays. Except for 2020 and 2021, the percentage of delayed flights for different lengths of delays and scheduled departure times did not significantly change across the review years. The evaluation reason for delay appeared to increase with time due to airport or authority restrictions, while there was a tendency for the number of delayed flights related to technical aircraft, equipment, and ground operations to decrease. By developing an analysis of the root causes of flight delays using case studies that have already been published by different researchers and determining the degree to which an operating parameter contributes, we may provide guidelines for future studies that will uncover ways to minimize flight delays.

Keywords: *contingency table, correspondence analysis, flight delays, reason for delay*

Abstrak

Berbagai risiko dapat terjadi karena kompleksitas dan sifat dinamis dari operasi transportasi udara. Dalam bisnis penerbangan, gangguan dapat terjadi karena berbagai sebab, antara lain cuaca buruk, mogok kerja, dan faktor politik. Tujuan dari penelitian ini adalah untuk menganalisis penundaan penerbangan yang dihadapi maskapai penerbangan Eropa dan menilai ketergantungan antara berbagai parameter operasi melalui analisis korespondensi dalam tabel kontingensi yang direpresentasikan secara visual menggunakan peta korespondensi. Studi ini mengkaji data dari salah satu maskapai penerbangan di Eropa antara tahun 2018 dan 2022, yang memuat informasi lama keterlambatan, alasan terkait keterlambatan, dan karakteristik spesifik setiap penerbangan, seperti jenis penerbangan, jenis pesawat yang digunakan, dan jadwal keberangkatan. Hasilnya menunjukkan bahwa meskipun terjadi penurunan besar pada keseluruhan jumlah penerbangan yang dioperasikan selama periode pandemi pada tahun 2020 dan 2021, tetapi persentase seluruh penerbangan yang tertunda tetap bervariasi lebih dari 55%. Penerbangan jarak jauh dan pesawat berukuran besar cenderung mengalami penundaan yang lebih lama. Kecuali tahun 2020 dan 2021, persentase penundaan penerbangan untuk durasi penundaan dan waktu keberangkatan terjadwal yang berbeda tidak berubah secara signifikan sepanjang tahun peninjauan. Evaluasi penyebab penundaan tampaknya meningkat seiring waktu karena pembatasan oleh otoritas bandara, sementara ada kecenderungan jumlah penerbangan tertunda terkait kondisi teknis pesawat, dan operasi ramp handling menurun. Dengan mengembangkan analisis penyebab penundaan penerbangan menggunakan studi kasus yang telah dipublikasikan oleh berbagai peneliti dan menentukan sejauh mana kontribusi parameter operasi, kami dapat memberikan pedoman untuk studi di masa depan yang akan mengungkap cara meminimalkan penundaan penerbangan.

***Kata kunci**: analisis korespondensi, keterlambatan penerbangan, penyebab keterlambatan, table kontingensi.*

1. Introduction

According to the IATA report in 2023, European airlines were in charge of 30.7% of total passenger traffic, followed by North American and Asia-Pacific airlines with 28,9% and 22,1%, respectively. The likelihood of delayed flight rises with traffic, making European travel particularly susceptible to delays. At periods of high traffic volume, demand is limited by several capacity constraints on European airspace, and the Russian invasion of Ukraine in February 2022 has made matters worse by extending the airspace restrictions [1]. On a larger scale, Air Traffic Flow and Capacity Management (ATFCM) employs a

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seamless process that extends from strategic planning to operations to guarantee that airport and airspace capacity satisfy traffic demand while optimizing traffic flows to prevent exceeding the available capacity when it cannot be further increased [2].

Nowadays, flight delays have developed into a recurring and expensive issue for airlines, airports, and passengers, resulting in considerable inconveniences and monetary losses [3]. The main objectives of this study are to determine the causes of flight delays and examine how they have evolved over the period from 2018 to 2022 for selected airlines [4]. It tries to quantify the amount of contribution from many factors that contributed to delays in air travel, including the scheduled departure time, the duration of delays, the aircraft utilized and the type of flight. It also reviews previous studies that are relevant to the subject of aircraft delays. By using historical data, this study aims to improve the understanding of delay trends, which will be useful in formulating strategies to help airlines avoid flight disruptions.

Airline on-time performance or punctuality, is certainly one of the most important indicators of airline quality because it is frequently used as a standard for the effectiveness and quality of airlines. There is a nonlinear correlation when system capacity is approached by demand as shown in Figure 1 [5]. Without significant improvements to aviation infrastructure, if demand in the system is currently in “D1” with delay at “delay1” level, for example, increasing demand to “D2” is likely to result in flight delays that are significantly longer than any we have previously encountered “delay2”. Thanks to capital investments, research, and development, the future system capacity scenario will move the rising demand “D3” while minimizing the effect of delay on “delay3” so the operator can provide better service to the passengers.

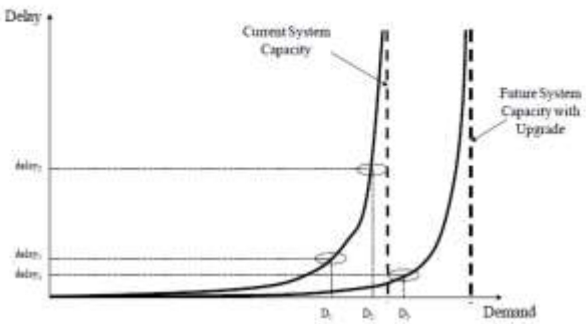

Figure 1 Diagram showing how demand, delay, and system capacity interact
Source: [5]

A calculated take-off time (CTOT) is used to control flights, which provides an Air Traffic Flow and Capacity Management (ATFM) “slot.” The ATFM designates a limited window of time between 5 and 10 minutes before and after the CTOT as the “slot” during which an aircraft may take off. The amount of time between the airline’s intended take-off time (in the flight plan) and the CTOT issued by Eurocontrol [6] affects whether the departure time is delayed. Any change to the expected off-block time (EOBT) of a filed flight plan that lasts more than 15 minutes must be communicated to the network manager’s integrated flight plan filing system (IFPS), as Eurocontrol is responsible for ATFCM in European airspace. Numerous studies have been done on the factors influencing flight delays in European traffic, including distributions of the duration of the delay by flight time and correlations between the cause and the length of the delay [7]. A notable gap in the current literature is the lack of studies that explicitly investigate how external factors, like the COVID-19 pandemic, affect flight delay trends. During this time, there were significant changes to the worldwide aviation scene that brought up new difficulties and disruptions. This study aims to incorporate the impact of the pandemic on the overall delay patterns in addition to filling in the knowledge gaps about normal delays. It is expected that the results of this study will offer significant perspectives to regulators, researchers, and airline operators. These perspectives will inform focused approaches to address delays, adjust to evolving situations, and improve the general effectiveness of European airline operations in the aftermath of the pandemic.

The investigation quality of service for European airlines, study [8] looked at different delay-mitigating techniques that varied between hub-and-spoke and point-to-point network structures. Service quality was measured by the average arrival delay in minutes. Their findings support the idea that airlines, especially if the flights begin at their hub airport, are more capable of managing delays if they hold a dominant position in the hub. Other studies conducted statistical analysis on arrival delays at several UK airports between 2018 and 2020, creating a method to analyse both mean delays and extreme events among airlines and airports and identifying a power-law decrease in significant delays [9]. Similar research used questionnaires and interviews to examine the causes of delays, determine which delays are acceptable, and assess the potential effects on British Airways customers' loyalty [10].

For further information regarding the factor of delay, Table 1 provides a list of prior studies concerning aircraft delays, classified according to their objectives, methodological concepts, and distinguishing characteristics

***Table 1** Delay factors in the current study*

Factors of delay	Related work	Research objectives	Methodology	Features
Airport ground service	Yıldız et al. (2022) [11]	Develop a system based on vision and machine learning to determine the real response times of the ground services	Employed streaming computer vision and deep learning, which used datasets from real-life airport turnaround cases and in-house-developed algorithms	Allowing the timing of ground services to be tracked and time stamped also might significantly improve airport ground service management and lower the expenses related to delays.
	Gladys et al. (2022) [12]	Identified the two main issues that arise when handling aircraft on the ground for several low-cost air carriers. The first is identifying delays in ground handling that affect when ground handling is supposed to be finished. The second issue is measuring the increased fuel use of aeroplanes to determine how these disturbances harm the environment.	The ground handling model used was developed using Simio software. Real operation data containing the performance of individual activities during ground handling starts from touchdown until pushback.	The simulation that was run showed that altering the likelihood of interruptions having an impact on the important chain activities results in longer execution times for these tasks, which in turn extends the entire ground handling procedure. It has been noted that even brief interruptions have the power to alter the direction of airlines' crucial routes. According to various simulation scenarios, the proportion of the dominant route, such as deboarding-refueling or cleaning-boarding, decreased from 70% to 59% while the proportion of the other alternatives increased.
Late passenger	Skorupski and Wierzbi´nska (2015) [13]	Provide a mathematical discrete model of the waiting time for late passengers that enables a satisfactory resolution. As well as calculating the expected value of the Passengers' Loss Time (PLT) about the random variable describing the late passengers' arrival time for boarding.	The boarding model (Dynamic Programming) utilized coordinated departure traffic data to explain the boarding procedure and the amount of time a late passenger would take.	Allow for the determination of a typical time, t max, at which the value of PLT, in the event of an instant end to waiting, equals the amount of time lost if the late passenger comes for boarding at time t max. When figuring out when to cease waiting, it may be helpful to compare the time tmax with the predicted value of the random variable that describes the time of arrival of the last passenger. Give examples of situations where it is justified to be patient and wait for a late passenger without incurring additional fees.
Air traffic	Takeichi (2017) [14]	Provide numerical traffic control simulations and statistical analysis of the delay accumulation behaviour utilizing the starting traffic statistics and the relationship	Utilized numerical optimization using MATLAB Optimization Toolbox to analyse arrival time controlled by changing flight path angle, which perturbations such as wind	Showed that when the arrival time error at the initial point of the arrival management is significant, the minimal flight time becomes the most effective nominal flight time to meet both the lowest flying time and fuel consumption. When the arrival time inaccuracy at the

Factors of delay	Related work	Research objectives	Methodology	Features
		between flight time and fuel consumption.	and navigation error are neglected	starting point decreases, the optimal nominal flight time diverges from the minimal nominal flight time. From the initial traffic statistics, it is possible to quantitatively estimate the delay buildup behaviour. Since the nominal flight time and the delay are added to form the total flight time, the delay estimation allows for the nominal flight time to be optimized to have the mean flight time as close to the total flight time as possible while still incurring the least amount of operating expense.
	Belkoura et al. (2016) [15]	Understanding airborne delays through the demonstration of a methodology to evaluate the emergence of non-AFTM delays from historical data. Create a computational framework that analyses planned and actual radar trajectories to identify situations where an aircraft deviates from the original plan under the assumption of constant velocity which is perceived as a delay or loss of time	Pseudo-complementary cumulative distribution functions (CCDF) can be used to derive the distribution of delay magnitudes caused by individual events. This is calculated by dividing the total number of occurrences by the number of flights, and it shows the probability distribution of the size of the delay caused by each incident.	The method can recover as much time as is typically lost by positive events in a day's worth of time. A resilient nature seems to be reinforced by some favourable circumstances, such as low flight numbers (i.e., low sky congestion) and large take-off delays (implying a desire to recover delays during the en-route phase).
Airport capacity	Liu, Zhao and Delahaye (2022) [16]	Create a slot allocation model for 15 coordinated airports in China that aims to reduce congestion at airports while ensuring efficient and smooth traffic flow within the bounds of capacity. Create a solid optimization model that takes uncertainty, total displacement, and recourse functions into account at both the aggregate and individual levels.	The scheduling framework consists of two-stage robust mixed integer programming, which reflects strategic decision-making and is then solved using a Benders' Decomposition algorithm and Gurobi optimization solver to identify an allocation scheme in the worst-case scenario and minimise the total displacement and delay costs.	Obtain the decision-related data from the flight level to significantly minimize the computing effort and complexity while maintaining the quality of the solutions. Allowing for the anticipation of unknown information that might surface on the day of flight operations and taking it into account in advance of strategic decision-making strengthens the results.
Delay propagatio n	Brueckner et al. (2022) [17]	Using a simpler propagating departure delay technique and calculating their impact on arrival delays for individual aircraft without taking into account their primary causes. In other words, instead of focusing on whether the inbound flight's tardiness was brought on by earlier delay propagation, try to ascertain whether the outbound flight's	Used a scheduling model to derive the relationships that underlie the following empirical work, which then derives the equation relating arrival delays to departure delays, which underlies several regression formulas that relate propagated departure delays to inbound arrival delays and the ground buffer.	Empirical findings demonstrate that propagating departure delays contributes to arrival delays when the inbound flight's arrival delay exceeds the ground buffer of the succeeding flight. This occurs when several important factors are present. The contribution of propagated delays to late arrivals is then determined by comparing the size (or frequency) of such propagated delays to the size (or frequency) of arrival delays. Since this method concentrates on a single flight and its immediate predecessor rather than attempting

Factors of delay	Related work	Research objectives	Methodology	Features
		tardiness was brought on by the inbound flight's tardiness.		to track the origins of delay propagation back through the full sequence of preceding flights, it differs from earlier attempts to quantify the contribution of delay propagation.
Optimization methods	Wu and Truong (2014) [18]	By developing a more efficient delay coding scheme and reporting framework that the industry can quickly adopt globally, we can improve the current IATA delay coding system.	Conducted specific delay analysis tasks frequently carried out by airline analysts to evaluate the performance of each coding scheme using simulated schedule and delay data.	Automated data analytics and data mining can be facilitated by a coding system with a well-designed reporting style, and a better grouping of delay codes can reduce potential confusion at the data entry and recording phases.

2. Methodology

The first phase is reviewing the literature by gathering all studies that support the goals of the investigation. Data for the delay analysis was obtained from a selected European airline. The next stage is data preparation, which involves creating a contingency table. A common method for obtaining a graphical representation of the interdependence between rows and columns is correspondence analysis, which involves applying a generalized singular value decomposition to the standardized residuals of a two-way contingency table to reduce the space's dimensionality [19].

Correspondence analysis is performed with Minitab Statistical Software to find relationships between various characteristics, such as duration of delay, type of aircraft, type of flight, scheduled departure time, and the reason for the delay. The procedure can be described into five processes [20]:

Step 1. Set up hypotheses and determine the level of significance. The hypotheses of Pearson's chi-squared test between two categorical variables are:

H0: Two categorical variables are independent.

Ha: Two categorical variables are dependent

Step 2. Select the appropriate test statistic

The chi-square statistic is a well-known way to assess how much the counts in a contingency table deviate from what would be predicted if the row and column classifications were independent. The chi-square statistic (χ2) is computed using the following formula: eij denotes the expected count in the cell for row i, column j, and nij is the actual count Expected count (eij) in a cell is row mass multiplied by the column mass and divided by the total count in the table.

$$\chi 2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(n_{ij-} e_{ij})^2}{e_{ij}} \quad (1)$$

Step 3. Set up a decision rule.

The degrees of freedom (k) and the significance level determine the χ2 test decision rule. The χ2 statistic will be near zero and the observed and expected frequencies will have values that are similar if the null hypothesis is correct. The χ2 statistic will be significant if the null hypothesis is rejected.

$$k = (I-1) \times (J-1) \quad (2)$$

I: number of columns

J: number of rows

$$F(x,k) = \int_0^x \frac{1}{2^{(\frac{k}{2})} \cdot \Gamma(\frac{k}{2})} \cdot t^{(\frac{k}{2}-1)} \cdot e^{-t/2}\, dt \quad (3)$$

$$P(\chi 2 \geq x) = \int 1 - F(x,k) \quad (4)$$

F (x, k): cumulative distribution function (CDF) of the chi-square distribution at the point x with k degrees of freedom

P: the right-tailed cumulative probability of the chi-square distribution.

Γ(k/2): gamma function, which is used to calculate the normalization factor.

X critical = χ^2_α, df (5)

x crit: the critical value for the chi-square test.

χ^2_α, df: the quantile function of the chi-square distribution with a specified significance level (α) and degrees of freedom (df).

Step 4. Compute the test statistics. Using the observed data, compute the expected frequencies, and then determine the test statistic mentioned in Step 2.

Step 5. Conclusion

Interpret the key results for correspondence analysis output (correspondence map):

- Identify the number of principal components also known as principal axes, that account for the majority of the data's variations from the predicted values, and can be determined by calculating the proportion of inertia.
- Examine the principal component, which represents the positions of categories in the reduced-dimensional space. Categories that are closer to each other on the map are more similar in terms of their associations
- Analyse the associations between the categories. Stronger correlation categories contribute more to the overall chi-squared value, as indicated by their position further from the origin
- Measure the relationship between two categorical variables with Cramer's value (V), which provides a value between 0 (representing no association between the variables) and 1 (perfect association). It can be classified as described in Table 2.

$$V = \sqrt{\frac{\chi 2}{n\,.((r,c)-1)}} \tag{6}$$

n: total number of observations.

r: number of rows in the contingency table.

c: number of columns in the contingency table

$$I_T = \frac{\chi 2}{n} \tag{7}$$

I_T : Total Inertia

Table 2 Interpretation of Cramer's Value

Cramer's value	Interpretation
>0.25	Very strong
>0.15	Strong
>0.10	Moderate
>0.05	Weak
>0	No or very weak

Source: [21]

3. Result and Discussion

The observed data was acquired in collaboration with a certain European airline that requested that writers anonymously publish the data over five years starting in 2018 until 2022, comprising over 225,000 flights [4]. The percentage of delayed flights for the considered time is displayed in Table 3.

Table 3 Proportion of delayed flights in the reference period

Period	Total Flight	All delayed flight (%)	Delayed Flight > 15min (%)
2018	76580	64.00	33.81
2019	70697	60.31	28.53
2020	14894	55.31	26.28
2021	14789	55.14	24.33
2022	48083	68.59	38.77

Sources: Authors' calculations,2023

Based on Table 3, the total number of flights operated was highest at the beginning of the reference period. However, due to the COVID-19 pandemic, which had a negative impact on the aviation industry as a whole in 2020 and 2021, there was a significant decrease in total flights, and they only gradually increased at the end of the reference period. The percentage of all delayed flights fluctuates around 55-60%, despite an approximately 80% reduction in total flights operated throughout the pandemic period.

3.1. Parameter 1 - Length of delay and aircraft type

The first association to be analysed is between the length of delay, which is divided into 6 categories, and the type of aircraft used in the operation, which consists of 23 aircraft as displayed in Table 4.

Table 4 Types of Aircraft Operated

No	IATA Code	Details
1	100	Fokker 100
2	223	Airbus A220-300
3	318	Airbus A318
4	319	Airbus A319
5	320	Airbus A320
6	321	Airbus A321
7	32A	Airbus A320 (sharklets)
8	332	Airbus A330-200
9	343	Airbus A340-300
10	359	Airbus A350-900
11	388	Airbus A380-800
12	772	Boeing 777-200 / 200ER
13	77W	Boeing 777-300ER
14	789	Boeing 787-9
15	AR1	Avro RJ100
16	AR8	Avro RJ85
17	AT4	Aerospatiale/Alenia ATR 42-300 / 320
18	AT7	Aerospatiale/Alenia ATR 72-201/-202
19	CR7	Canadair Regional Jet 700 | Regional Jet 550
20	CRK	Canadair Regional Jet 1000
21	E70	Embraer 170
22	E90	Embraer 190
23	ER4	Embraer RJ145

Source: Internal data of selected airlines

Table 5 illustrates the proportion of flights corresponding to the length of delay and aircraft operated from the total of flights during the 5 years from 2018 until 2022. Out of the 23 aircraft that were operated as indicated in Figure 2, Table 5 only showed the flights from 6 different types of aircraft.

Table 5 Contingency table for Length of delay and Sample of Aircraft type

Delay	332	343	388	772	77W	789
No delay	26.69%	30.12%	22.32%	33.16%	31.53%	29.25%
<15 min	26.2%	20.77%	23.21%	27.25%	26.60%	24.87%
15-30 min	17.3%	18.69%	19.64%	16.84%	17.92%	19.23%
31-60 min	18.9%	16.77%	20.09%	14.93%	15.93%	16.91%
61-120 min	8.12%	9.05%	10.94%	6.03%	6.18%	7.78%
> 121 min	2.69%	4.60%	3.79%	1.80%	1.84%	1.97%

Source: Authors’ calculations,2023

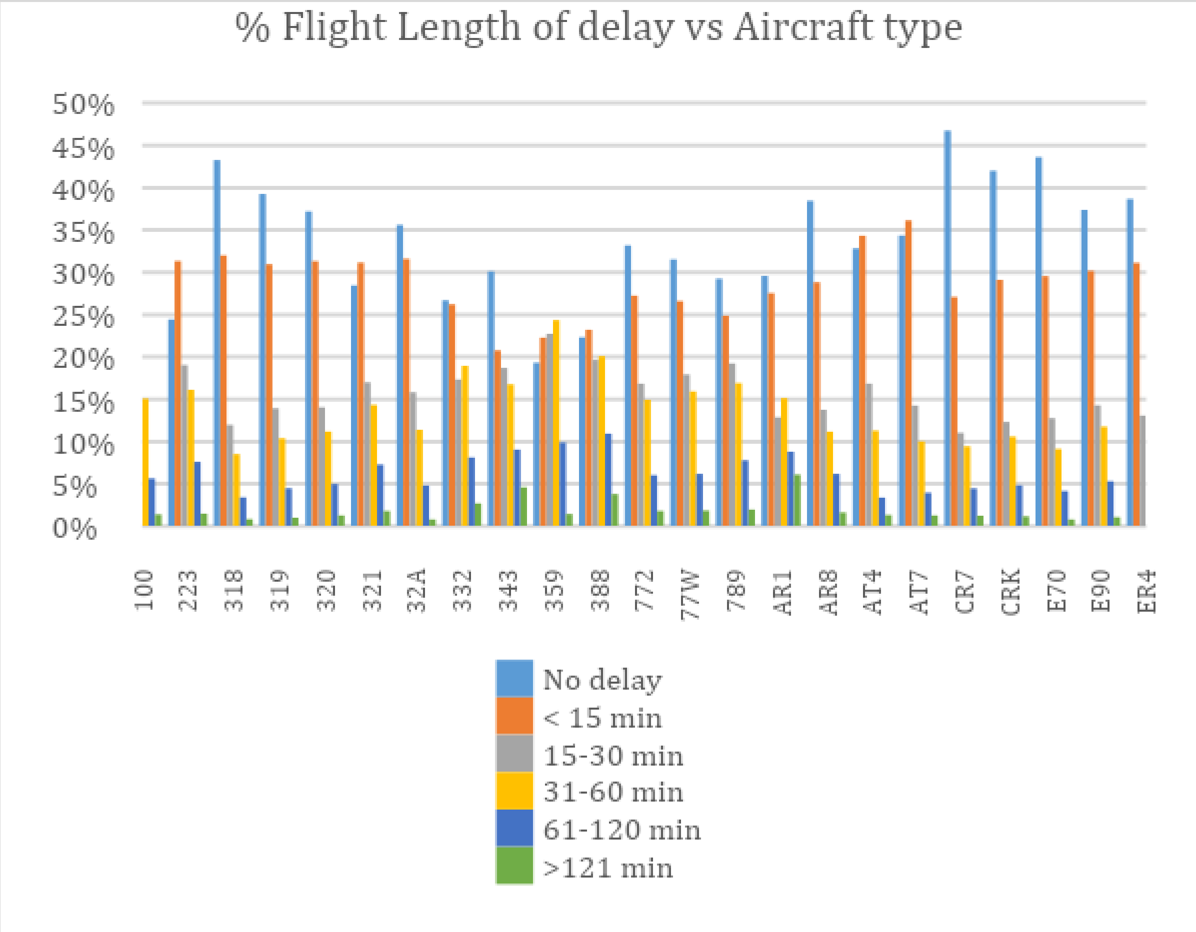

Figure 2 Proportion Flight Length of delay vs Aircraft type

Based on the correspondence analysis results obtained with the Minitab tool, it is determined that there is an association between the variables and that the null hypothesis of variable independence is rejected because the calculated chi-square value (4680.637) is greater than the critical value (135.480) or the p-value (0.000) is less than the significance level (0.05). However, based on the Cramer value (0.065), which is less than 0.1 indicates a weak level of dependence or correlation.

To find relationships, a correspondence map is used to interpret the principal components of either the row categories or the column categories, which are determined by coordinates in row and column contribution. The more influential categories are represented by points that are further from the original point. A component that opposes these categories is indicated by points on the opposing sides of the plot. The profiles are dispersed throughout the plot to make it easier to see the distances between them.

Components 1 and 2 in Figure 3 are the first two principal components of the data set. Component 1 explains the largest amount of information in the data with 85.53%, followed by component 2 with 8.98%. Therefore, if we only use the first two factors, we only lose 5.49% of the variation because they account for 94.51% of the variation from the total inertia.

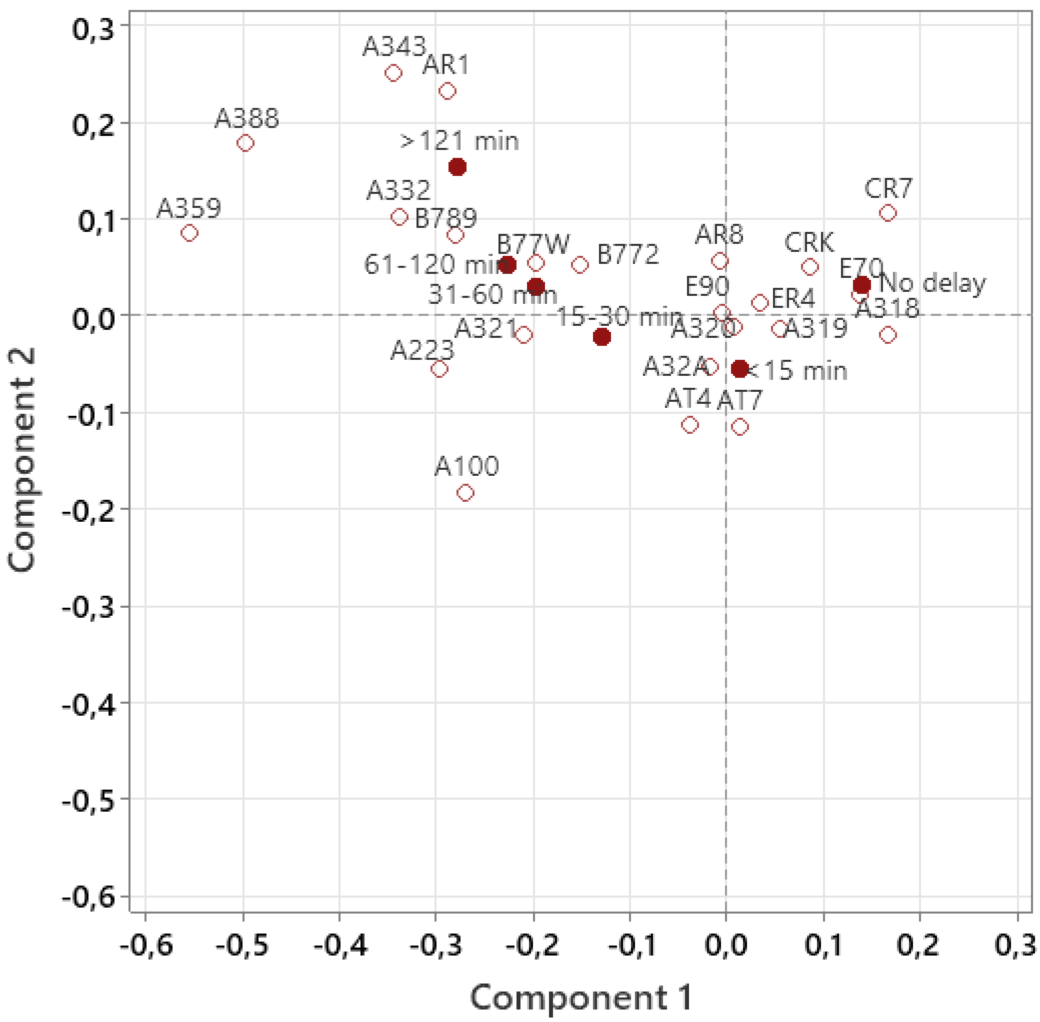

Figure 3 Correspondence Map for Length of delay and Aircraft type

Figure 3 shows that the delay lengths of 31– 60 min and 61–120 min are near together and have profiles in common. Additionally, there are similarities in the types of aircraft between the Airbus 318, 319 and 320, as well as the Boeing 777-200ER (772) and 777-300ER (77W) which are all situated in the same quadrant. Overall, this graph indicates that larger aircraft types, such as the Airbus 332, 343, 359, 388 or the Boeing 789, 77W, are primarily associated with delays of more than 30 minutes and prolonged delays of more than 2 hours. Additionally, there is a strong association between no delay and a delay of 15 minutes or less for smaller aircraft like the A318, 319, and Embraer aircraft like the E4, and E70. This conclusion agrees with [22] which found that smaller Boeing 737–500 and 737–700 aircraft frequently fly with little to no delay, but larger aircraft, like the Airbus A320, frequently experience extended delays of more than an hour.

3.2. Parameter 2 - Length of delay and type of flight

Table 6 List Type of Flight

No	Code	Details
1	LH	Long haul flight
2	MH HUB	Medium haul from HUB airport
3	MH P2P	Medium haul Point-to-point airport
4	CS	Code share alliance agreement

Sources: Internal data of selected airlines

Table 7 Contingency table for Length of delay and Type of Flight

Length of delay	LH	MH HUB	MH P2P	CS
No delay	30.13%	33.24%	44.61%	39.28%
1-15 min	25.83%	32.09%	29.45%	30.63%
16-30 min	17.89%	15.77%	11.63%	13.53%
31-60 min	16.89%	12.20%	9.16%	10.64%
61-120 min	7.09%	5.46%	4.18%	4.75%
>120 min	2.17%	1.23%	0.98%	1.16%

Sources: Authors' calculations

This parameter analysis is to find the correlation between the length of the delay and the type of flight, which is divided into the long haul, medium haul and codeshare operations. According to Table 7, medium-haul flights P2P have the best performance when it comes to delays, while long-haul flights typically have a longer duration of delay. The test statistic indicates that the calculated chi-square value (2613.392) is more than the critical value (31.410) or the p-value (0.000) is less than the significance threshold or significance level (0.05), hence rejecting the null hypothesis. The degree of correlation, however, suggests a weak degree of dependency based on the Cramer value (0.055), which is less than 0.1.

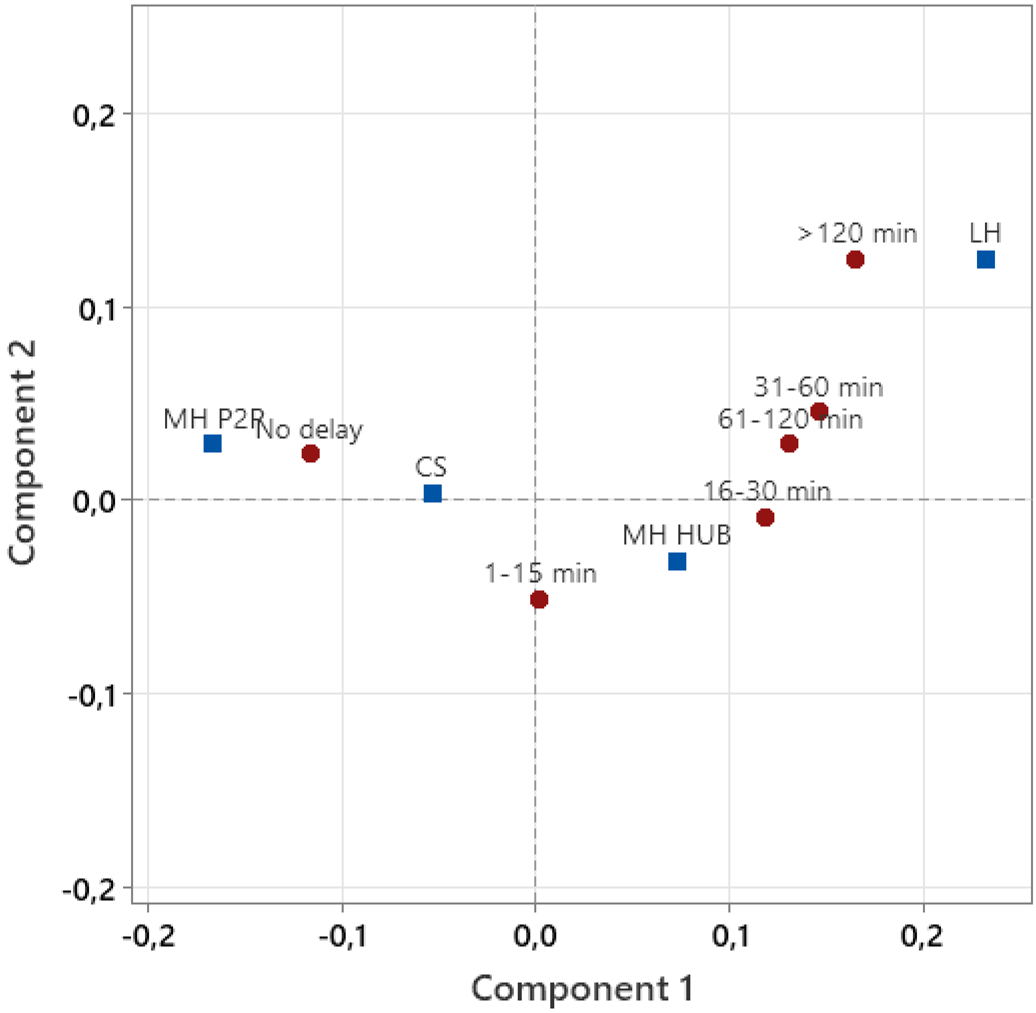

Figure 4 Correspondence Map for Length of Delay and Type of Flight

In Figure 4, Component 1 explains 87.67% of the total information in the data, followed by Component 2 accounts for 12.29%. Therefore, using the first two factors, they account for 99.96% of the variation from the total inertia.

The length of delay has shown the same trend as the previous parameter. Overall, Figure 4 indicates that LH flights are primarily associated with delays of more than 1 hour. Additionally, there is a strong association between MH P2P with no-delay flights. This is consistent with the analysis of parameter 1 since larger aircraft are typically employed for long-haul flights than for medium-haul flights due to the necessity to cover greater distances and take longer trips, often experiencing delays of more than 30 minutes.

3.3. Parameter 3 - Length of delay and reference period

Table 8 shows that even though the COVID-19 pandemic had a major impact on the numbers of passengers in 2020 and 2021, the quality of the flight itself was performing better, indicating a decrease in the number of short- or long-duration delayed flights and an increase in on-time performance. This statement is consistent with the study which discovered that in 2020, there was a decrease in both arrival and departure delays during the peak of rises in reported COVID-19 cases [23].

According to the test statistics, the null hypothesis regarding the independence of the variables is rejected since the calculated chi-square value (2806.796) is greater than the critical value (31.410) or the p-value (0.000) is less than the significance threshold or significance level (0.05). The Cramer value (0.056), which is less than 0.1, indicates a weak degree of dependency based on the degree of correlation.

Table 8 Contingency table for Length of delay and Reference Period

	2018	2019	2020	2021	2022
No delay	36.00%	39.69%	44.69%	44.86%	31.41%
<15 min	30.19%	31.78%	29.03%	30.81%	29.82%
16-30 min	14.91%	13.34%	12.10%	12.38%	16.08%
31-60 min	12.17%	9.69%	9.31%	8.85%	14.15%
61-120 min	5.40%	4.33%	4.02%	2.60%	6.99%
>121 min	1.32%	1.17%	0.86%	0.50%	1.56%

Sources: Authors' calculations

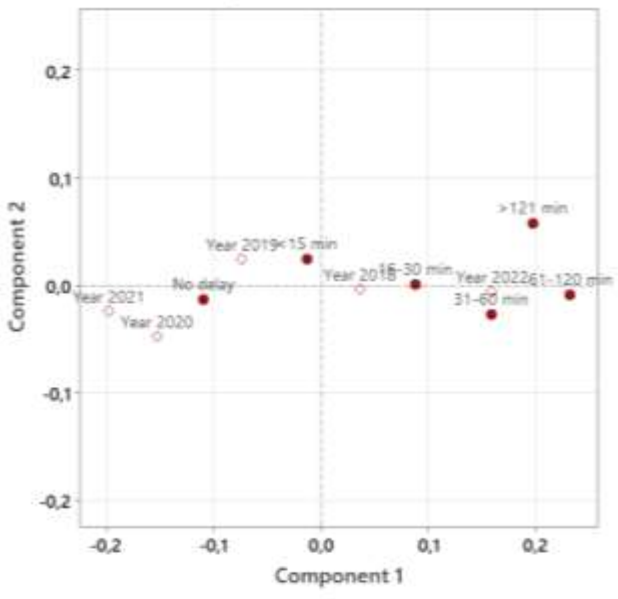

Figure 5 Correspondence Map for Length of Delay and Reference Period

Figure 5 represents 95.63% of the total information in the data from Component 1, and accounts for 3.09% in Component 2. Therefore, using the first two factors, they account for 99.71% of the variation from the total inertia. The correspondence map above shows that the delay lengths of 16-30 min, 31– 60 min and 61–120 min are close together and have profiles in common. Additionally, there are similarities in the period 2020 and 2021, which are all situated in the same quadrant. Overall, the trend of delayed flights of more than 15 minutes to 2 hours is more associated with the period in 2018 and 2022, which is the normal period without any peculiar conditions like the pandemic COVID-19. While COVID-19 impacted in 2020 and 2021, is more associated with no delay.

3.4. Parameter 4 - Scheduled Departure Time and Reference Period

Table 9 indicates that during the reviewed years, there was no significant change in the proportion of delayed flights at any time of day. This aligns with the findings of [22]. The sole variation occurred in 2020 and 2021, with a minor decrease in evening hours.

Table 9 Contingency table for Departure Time and reference period

	2018	2019	2020	2021	2022
0:01-6:00	1.08%	1.75%	2.44%	2.32%	2.62%
6:01-12:00	37.24%	39.59%	45.92%	43.28%	38.41%
12:01-18:00	39.28%	38.09%	34.23%	38.74%	38.80%
18:01-24:00	22.40%	20.56%	17.41%	15.67%	20.18%

Sources: Authors' calculations

The statistical test computation indicates that there is a significant association between the variables because the calculated chi-square value (1238.309) is greater than the critical value (21.026) or the p-value (0.000) is less than the significance threshold or level (0.05). This means that the null hypothesis of the variables' independence is rejected. However, based on the degree of correlation, the Cramer value (0.043), which is less than 0.1, shows a weak degree of dependency.

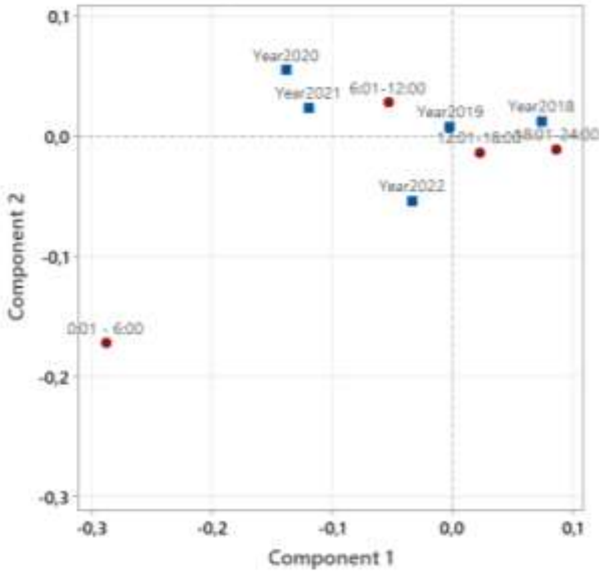

Figure 6 Correspondence Map for Scheduled Departure Time and reference period

Component 1 in Figure 6 represents 78.4% total variation in the data, while component 2 accounts for 16.87%. Therefore, using the first two factors, they account for 95.26% of the variation from the total inertia. There are widely dispersed profiles in both the rows and the columns of the map above, indicating that no two profiles are similar. Thus, the sole noteworthy correlation with the highest percentage of delayed flights occurred during the morning hours of 2020 and 2021. The row categories for 18:01–24:00 and 00:01–16:00, indicate the furthest point from the origin but with opposing signs, which means both have contradicted profiles, similar to column profiles 2018 and 2020.

3.5. Parameter 5 - Reason of delay and Year Period

Table 10 summarizes IATA delay codes and reasons for delay. Table 11 indicates the annual distribution of delay from 2018 to 2022.

Table 10 List Reason for Delay

Code	**Details**	**Example**
AIC	Airlines Internal Codes	No gate/stand availability due to own airline activity
PB	Passenger and baggage	Late check-in, over-sales, commercial publicity, reduced mobility, etc
CM	Cargo and Mail	Late positioning or late acceptance of cargo and mail
ARH	Aircraft and Ramp Handling	Loading/unloading, fuelling, catering, cleaning

Code	Details	Example
TAE	Technical and Aircraft Equipment	Aircraft defect, maintenance, spare part, aircraft change due to technical reason
FOC	Flight Operations and Crewing	Late completion or change of flight documentation, operational requirement, late crew boarding
WEAT	Weather	Significant weather conditions at departure, destination, de-icing
ATFM	ATFMR	ATC en-route capacity limitation or constraint
AGA	Airport And Governmental Authorities	Security, immigration, airport facilities, etc
RC	Reactionary	Load connection, late arrival from previous flight, operation control
MSC	Miscellaneous	Industrial action, other reasons

Source: [24]

Table 11 Contingency table for Reason of Delay and reference period

	2018	2019	2020	2021	2022
AIC	0.84%	1.09%	0.67%	0.92%	0.56%
PB	9.97%	7.91%	5.71%	8.02%	10.81%
CM	0.10%	0.09%	0.07%	0.09%	0.18%
ARH	7.63%	7.42%	4.61%	5.76%	6.58%
TAE	3.75%	3.57%	3.06%	2.65%	3.55%
FOC	3.51%	2.71%	2.09%	2.33%	3.68%
WEAT	1.32%	0.85%	0.97%	0.93%	1.10%
ATFM	54.91%	58.96%	66.04%	51.75%	51.59%
AGA	9.14%	9.29%	7.54%	20.58%	13.45%
RC	8.52%	7.53%	7.78%	5.19%	6.99%
MSC	0.30%	0.57%	1.47%	1.78%	1.52%

Sources: Authors' calculations

The trend of total delays fluctuated during the reference period, with air traffic constraints, or ATFM, being responsible for more than half of the delays. During the COVID pandemic that struck in 2020 and 2021, there was a downward trend in the number of delays brought on by flight or ground personnel, passengers, and baggage. This makes sense because fewer people are travelling during this period, keeping the staff and aircraft in good condition and ready for service. During the reference period, the ratio of delayed flights to total delayed flights is rising due to AGA, with the other reason just slightly changing.

Due to the fact calculated chi-square value (2993.561) is greater than the critical value (55.758) or the p-value (0.000) is less than the significance threshold or level (0.05), the statistical test computation shows that there is a significant relationship between the variables. Thus, the null hypothesis regarding the independence of the variables is rejected. Nonetheless, the Cramer value (0.073), which is less than 0.1, indicates a weak degree of dependency based on the degree of correlation.

Component 1 with 64.28% and Component 2 (26.08%) in Figure 7 accounted for the cumulative variation of 90.36% from a variation of total inertia. There are widely dispersed profiles in the columns of the map figure, indicating that no reference period is similar. The row categories for AIC and MSC indicate furthest from the origin with opposing signs. Row categories for ARH, TAE, and RC are close to one another, indicating a tendency toward similar characteristics.

Table 11 demonstrates that while the percentage of ARH, TAE, and RC for delay declined during the reference period, it also reveals that the percentage peaked in 2018. Figure 7 indicates that the majority of the ATFM-related delay is linked to the year 2020, while the AIC is more closely linked to the year 2019. This contrasts with the findings [22] which discovered that whereas ATFMR was more common in previous years, AIC, ARH, TAE, and AGA have been more common in recent years. In this study, ARH and TAE have tended to decline with time.

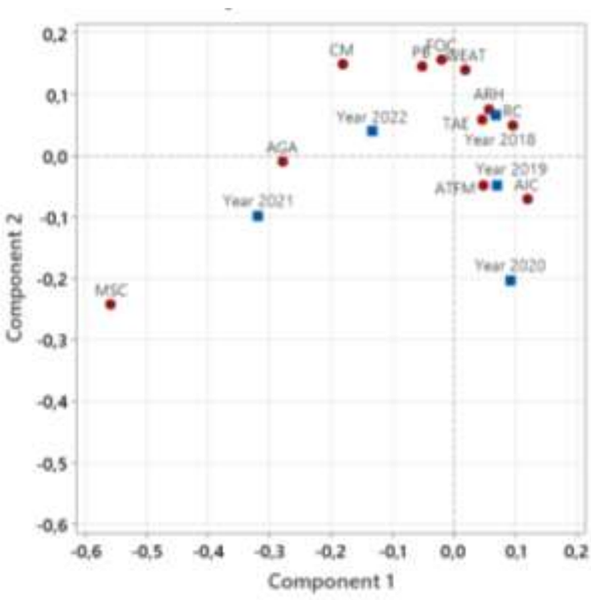

Figure 7 Correspondence Map for Reason of Delay and reference period

The overall impact of a flight delay will be significant, not only in terms of increased fuel requirements, airport fees, and flight crew member pay but also in terms of greater operation costs incurred by compensating passengers [3]. In addition to immediate losses, flight delays may generate future losses and harm an airline's reputation since passengers may consider airlines with frequent delays as unreliable or unprofessional, resulting in a decline in demand for their services [25]. As a result, analysing the correlation between the operating parameters is critical for understanding the trend and developing an avoidance strategy. The majority of the parameters analysed in this study were also examined by [7] and [22], who conducted a similar study evaluation of the factors impacting flight delays for European airlines. A comparable outcome was seen with the correlation between the duration of the delay and the type of aircraft. Larger planes are more closely associated with longer delays; our research goes deeper into the variables of flight type. Consistent with the first parameter result, long-haul flights also have a higher risk of longer delays because larger aircraft are typically used for these types of flights. This is because longer flights and larger aircraft require more time for ground operations. Consequently, if an aircraft arrives late or there is a rotational delay, one delayed long-haul flight can have a domino effect on the entire schedule, resulting in additional delays and cancellations.

When compared to the same medium-haul route but operated out of HUB airport, there are fewer delays on medium-haul point-to-point flights. This is because hub airports are typically busier. Based on historical data analysis, a study by [6] that analysed delays in Spanish airports in 2017–2018 discovered that hub airports (Madrid and Barcelona) experienced a higher frequency of arrival delays for all causes of delays than non-hub or small airports. According to [26], planes arriving at a hub require an additional 1.5 to 4.5 minutes of delay, and flights leaving from hub airports require between 4 and 7 minutes of extra travel time.

Since 2018 to 2022 is the reference year utilized in this study, it can also be used to determine the trend of delay during the COVID-19 pandemic era. Therefore, comparing the COVID-19 impact on global scheduled passenger traffic for the years 2020 and 2021 to 2019 levels is a useful side project of our research. The characteristics of air transport operations during the COVID-19 pandemic, such as the quality of the flight itself, performed better, indicating a decrease in the number of short- or long-duration delayed flights and an increase in on-time performance with a minor decrease in evening hours' flight delay. Furthermore, there was a downward trend in the number of delays due to flight or ground personnel, passengers, and baggage. This pattern differs from the regular years of 2018, 2019, and 2022, where the decline is attributed to aircraft ramp handling, technical issues with the aircraft, and reactionary delays. This is somewhat in contrast to the findings which showed that crew duty, technical maintenance or aircraft defects, airline operational suppliers such as handling, fuelling, or catering, and lastly delays due to previous flights have steadily increased [22]. The only commonality is the increase in delays brought on the airport constraints.

Understanding this delay trend has implications for airlines, such as motivating airlines to conduct deeper studies related to predictive analytics to optimize turnaround times and reduce the risk of delays. The prediction approach reveals characteristics that affect upcoming delays, enhancing airline comprehension of system behaviour. There is also increasing awareness for airlines to invest in advanced scheduling and planning to accommodate the special needs of larger aircraft. Airlines and airports may also work together in collaborative decision-making (A-CDM) to improve the efficiency and resilience of airport operations by optimizing the use of resources and improving the predictability of air traffic. It encourages the airport partners (airport operators, aircraft operators, ground handlers, and ATC) and the network manager to work more transparently and collaboratively, exchanging relevant, accurate, and timely information. It focuses especially on aircraft turn-round and pre-departure processes within the European ATFCM network, leading to improved en-route and sectoral planning [27]. In the long-term plan, airlines can work together with airports to improve infrastructure. This could include expanding runways, streamlining taxi routes, and upgrading terminal facilities to handle the operating demands of larger aircraft. Airlines should also engage in discussions with government officials to better understand regulatory changes, provide feedback on potential consequences, and collaborate to create solutions that balance safety and operational efficiency. Participation in industry alliances and advocacy organizations can indeed assist airlines in collectively addressing structural difficulties in Europe. Airlines for Europe (A4E), for example, is an organization that represents the interests of European airlines. It aims to advance its members' interests and fight for policies that promote a competitive and sustainable aviation industry in Europe [28]. Airlines may help to set rules that balance safety and efficiency by consulting with regulatory groups regularly.

The output of the correspondence analysis of the delay factor (correspondence map) offers an illustration that is simple to use and straightforward, so it is more applicable in the workplace for explaining the delay trend to the management. Decision-makers can find patterns, correlations, and clusters in the data with the use of this mapping. In the end, it will give regulators and airline operators useful information about how to better allocate resources, create focused mitigation plans for certain delay factors, and modify operations in response to dynamic conditions.

This study is limited to assessing correlations between two categorical variables, which are commonly represented in a contingency table, and may encounter difficulties when dealing with sparse data or variables with multiple categories and low frequencies. To overcome this limitation, future work can focus on multidimensional correspondence analysis (MCA), which can handle more than two category variables at the same time, enabling the analysis of higher-dimensional data sets in the future. This makes MCA more adaptable for investigating complex interactions [29]. MCA is generally more effective in dealing with sparse data because it incorporates several variables, which can aid in capturing more information and correlations in the data.

4. Conclusion

This study contributes to filling a literature gap caused by a lack of studies that explicitly investigate how external factors, such as the COVID-19 pandemic, affect flight delays because there were significant changes in global aviation during this period that introduced new challenges and disruptions. The goal of this study is to determine the factors that have caused flight delays over time and to analyse the trends in flight delays between 2018 and 2022. The trend showed that larger aeroplanes are associated with longer delays, the proportion of delayed flights did not change significantly during the years under review at different times of the day, and the reason for flight delays caused by airport restrictions slightly increased during the study period. During the COVID-19 period that affected the aviation business in 2020 and 2021, the highest percentage of delayed flights occurred during the day, and there was a trend toward reducing delays due to flight crew management, passengers, and baggage, aircraft and ground handling.

The correspondence map gives a user-friendly illustration as an outcome, making it more useful in business. This mapping can be used as a guideline by companies to better allocate resources, develop targeted mitigation, and modify operations. This study may have progressed in the future by examining different variables and using multidimensional correspondence analysis to look for connections between more than two variables, making it useful for exploring complex relationships.

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