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UNIVERSIDADE Ð COIMBRA

Pedro José Freitas Reis

PREDICTING AIR PASSENGER SATISFACTION:
A MACHINE LEARNING APPROACH

Dissertation in the context of the Master in Management, supervised by Professor Joana Maria Pina Cabral Matos Dias and presented to the Faculty of Economics of the University of Coimbra

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To my mom,

I miss you every day.

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To my supervisor, Professor Joana Dias, for her unwavering guidance and invaluable support and advice throughout this dissertation.

To my Father and my Sister, for loving me and helping me unconditionally.

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Abstract

The air travel industry plays a crucial role in the global economy by fostering economic growth and promoting connectivity. Within this industry, airlines face various challenges, such as intense competition, cost management, environmental sustainability, and passenger satisfaction. Extensive research has been conducted to understand the relationship between service quality and passenger satisfaction, exploring dimensions such as punctuality, ease of online booking, and convenience of schedules.

The ability to predict passenger satisfaction is of great importance, as a considerable portion of passengers may not explicitly express their dissatisfaction to airlines. In this context, most of the current studies try to identify the impact of each service dimension on passenger satisfaction. While this approach may be useful for airlines to design or reformulate their product and service offerings, it is not as useful to predict overall satisfaction, since passenger satisfaction is typically influenced by a complex interplay between various service dimensions and demographic factors. Therefore, it is important to develop a model that can learn these complex relationships and use them to predict if a passenger was, in overall terms, satisfied or not.

With this in mind, this study uses a dataset from an airline survey, encompassing personal responses such as seat comfort and Wi-Fi service scores, as well as general factors like flight punctuality and distance, to develop two predictive models using Classification Machine Learning algorithms: one incorporating only general factors to which the airline has immediate access and another including personal responses. The performance of each model is compared to the performance of random guessing.

Remarkably, both models present strong predictive capabilities in determining passenger satisfaction when compared to random guessing. The model without personal responses achieved, in the test dataset, an average accuracy of 79%, with F1-Scores and AUC averaging at 0.76 and 0.84, respectively. Furthermore, the model incorporating personal responses achieved, also in the test dataset, even higher performance, with an average accuracy of 93% and F1-Scores and AUC averaging at 0.92 and 0.97, respectively. The Random Forest algorithm proved to be the most effective in both models, highlighting

its significance in uncovering hidden patterns and establishing connections between seemingly unrelated variables.

This study demonstrates that even in the absence of explicit features indicating passenger satisfaction with specific service dimensions, it is still possible to predict overall passenger satisfaction with a satisfactory level of accuracy. By using machine learning algorithms, airlines can effectively identify which passengers were dissatisfied with their experience, allowing them to take proactive measures to address any issues or concerns.

This capability enables airlines to enhance customer satisfaction and elevate the overall passenger experience by paying more attention to individual passenger satisfaction and taking proactive measures to address their needs. As a result, airlines can improve their customer service efforts and foster positive customer relationships, increasing loyalty. These findings contribute to the continuous pursuit of passenger focused strategies within the aviation industry, emphasizing the importance of placing passengers at the center of all decisions and attempting to, at least, meet their expectations throughout their journey.

Keywords: Airline Industry, Air Passenger Satisfaction, Machine Learning, Classification Algorithms

Resumo

A indústria das viagens aéreas desempenha um papel crucial na economia global fomentando o crescimento económico e promovendo a conectividade. Nesta indústria, as companhias aéreas enfrentam diversos desafios como a competição intensa, gestão de custos, sustentabilidade ambiental e a satisfação dos passageiros. Muita pesquisa foi desenvolvida no sentido de compreender a relação entre a qualidade de serviço e a satisfação dos passageiros, explorando dimensões como a pontualidade, facilidade de reserva online e conveniência dos horários.

A capacidade de prever a satisfação dos passageiros é de extrema importância, uma vez que uma parte considerável de passageiros pode não exprimir a sua insatisfação às companhias aéreas. Nesse contexto, a maioria dos estudos atuais procura identificar o impacto de cada dimensão de serviço na satisfação dos passageiros. Embora essa abordagem possa ser útil para as companhias aéreas desenvolverem ou reformularem os seus produtos e serviços, a mesma já não é tão útil para prever a satisfação geral, uma que vez que a satisfação dos passageiros é tipicamente influenciada por uma interação complexa entre diversas dimensões de serviço e variáveis demográficas. Portanto, é importante desenvolver um modelo capaz de aprender essas relações complexas e utilizá-las para prever se um passageiro ficou, em termos gerais, satisfeito ou não.

Com isto em mente, este estudo utiliza um conjunto de dados de um inquérito realizado junto de uma companhia aérea, que engloba avaliações pessoais, tais como conforto dos lugares e pontuações do serviço Wi-Fi, bem como fatores gerais tais como a pontualidade dos voos e a distância percorrida, para desenvolver dois modelos preditivos utilizando algoritmos de Aprendizagem Computacional de Classificação: um incorporando apenas fatores gerais, e o outro incluindo avaliações pessoais. A performance de cada modelo é comparada com a performance de adivinhar aleatoriamente.

Notavelmente, ambos os modelos apresentaram fortes capacidades preditivas em determinar a satisfação do passageiro, quando comparado com adivinhar aleatoriamente. O modelo sem avaliações pessoais alcançou, no conjunto de teste, uma precisão média de 79%, com *F1-Scores* e *AUC* de 0.76 e 0.84, em média, respetivamente. Além disso, o modelo incorporando avaliações pessoais alcançou, também no conjunto de teste, uma performance

ainda mais elevada, com uma precisão média de 93%, e *F1-Scores* e *AUC* de 0.92 e 0.97, em média, respetivamente. O algoritmo *Random Forest* provou ser o mais eficaz em ambos os modelos, revelando a sua importância na identificação de padrões ocultos e no estabelecimento de ligações entre variáveis aparentemente não relacionadas.

Este estudo demonstra que, mesmo na ausência de características explícitas que indiquem a satisfação dos passageiros com dimensões de serviço específicas, ainda assim é possível prever a satisfação geral dos passageiros com um nível satisfatório de precisão. Ao utilizar algoritmos de aprendizagem computacional, as companhias aéreas podem identificar efetivamente quais os passageiros que ficaram insatisfeitos com a sua experiência, permitindo que tomem medidas proativas para resolver quaisquer problemas.

Esta capacidade permite que as companhias aéreas melhorem a satisfação do cliente e que elevem a experiência geral dos passageiros, dando mais atenção à satisfação individual do passageiro e tomando medidas proativas para atender às suas necessidades. Como resultado, as companhias aéreas podem melhorar os seus esforços de serviço ao cliente e promover relacionamentos positivos com o mesmo, aumentando a fidelidade. Estes resultados contribuem para a procura contínua de estratégicas focadas no passageiro na indústria da aviação, enfatizando a importância de colocar os passageiros no centro de todas as decisões e tentar, no mínimo, satisfazer as suas expectativas ao longo das suas viagens.

Palavras-Chave: Indústria da Aviação, Satisfação do Passageiro de Transporte Aéreo, Aprendizagem Computacional, Algoritmos de Classificação

List of abbreviations and acronyms

AI	Artificial Intelligence
ASA	Air Service Agreements
AUC	Area Under the Curve
DT	Decision Tree
EU	European Union
FFP	Frequent Flying Programs
FSA	Full-Service Airlines
GDP	Gross Domestic Product
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
KNN	K-Nearest Neighbors
LCA	Low-cost Airlines
LR	Logistic Regression
MARS	Multivariate Adaptive Regression Splines
ML	Machine Learning
NCAA	National Civil Aviation Authority
NNet	Neural Networks
RF	Random Forest
ROC	Receiver Operating Characteristic
SAF	Sustainable Aviation Fuel
SARS	Severe Acute Respiratory Syndrome
SVM	Support Vector Machines
USA	United States of America

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Introduction

There is a large body of research, both theoretical and practical, that has been conducted on the effects of transportation on the economy (Banister, 2012; de Almeida & de Mendonça, 2019; Melo et al., 2013; Mohmand et al., 2017; Pradhan, 2019; Pradhan & Bagchi, 2013; Tong & Yu, 2018). Overall, the literature indicates that transportation has a positive impact on the economy, with certain modes of transportation having a more significant effect than others.

Nonetheless, the effects of aviation on economic growth have not been extensively studied since it is hard to determine the causal relationship between aviation and the economy due to the complexity of modelling this relationship (Carbo & Graham, 2020). This arises from the fact that air transport is considerably endogenous to economic activity (AitBihiOuali et al., 2020), meaning that air transport is dependent on the economic activity, but the economic activity is also dependent on the air transport.

In every industry, with the air travel industry being no exception, guaranteeing customer satisfaction is of utmost importance. Consumer satisfaction is an outcome of a purchase or consumption that results from the customer weighing the advantages versus the expenses as well as the expected outcomes. It may be defined as the total happiness resulting from different product and/or service qualities (Churchill & Surprenant, 1982).

In order to maintain customer satisfaction and thereby future revenue in the fiercely competitive airline sector, good customer relations management is required. Particularly, passenger feedback is important because it acts as a driver for companies' performance (this is why companies usually collect data through customer surveys), customer experience enhancement, and the development of new products and services (Morgan & Rego, 2006; Siering et al., 2018).

Airlines must continue to satisfy customers and convert that contentment into behavioral commitment in order to stay relevant. Otherwise, they risk losing their customers to the competition, which would not be too hard considering how competitive this industry is[1].

However, unsatisfied customers not always share their feedback with companies due to, for example, the aversion to criticize others (Hydock et al., 2020). As consumers often perceive brands as human-like entities, it is likely that those who are dissatisfied with a brand will avoid expressing their negativity towards it.

According to Deloitte, 81% of individuals consult reviews and ratings. Additionally, over a third of consumers participate in online forums or leave comments on blogs. Also, Deloitte indicates that for most consumers, the most trustworthy sources of information are recommendations from family and friends, as well as consumer reviews (Perkins & Fenech, 2014).

By this means, it can be stated that (1) consumers are willing to share their experiences (good or bad) online and (2) a great majority of people reads those experiences. Therefore, if a company does not find ways to manage customer's experiences (specially the bad ones), there is a greater probability that they will influence others, even if indirectly, to step away from the company.

In light of this, companies should not just rely on that customers will come to them to tell them their bad experiences, or even reply to a survey, for the record. With this in mind, this dissertation aims to address two primary objectives. Firstly, it seeks to understand some of the factors and dimensions that might be relevant for passenger satisfaction, encompassing various aspects ranging from socio-demographic factors to service-related factors such as seat comfort, entertainment options, the performance of cabin crew, punctuality, safety, among others. Secondly, it aims to develop a predictive model that uses some of the identified factors to determine whether a passenger is likely to be satisfied or dissatisfied with his/ her experience. This allows the airline to act proactively to (1) compensate unsatisfied passengers in some way, and (2) change any aspect that could improve the overall experience for all passengers.

[1]To illustrate, at the time of writing there were 5 airlines operating the route between Lisbon and Madrid, Amsterdam, and Paris (https://www.flightsfrom.com/ , January 2023)

This dissertation is structured into several chapters, each focusing on different aspects related to the air travel industry and passenger satisfaction. After the introductory section, Chapter I provides an overview of the air travel industry, discussing its importance, characteristics, and the challenges faced by airlines in decision-making. Chapter II delves into the concept of air service quality and passenger satisfaction, exploring various dimensions of airline quality across reservation channels, flight conditions, inflight service, among others.

Chapter III focuses on predicting air passenger satisfaction, covering the sources of information for airlines and different machine learning classification algorithms. It also discusses good practices in machine learning, such as data pre-processing, training and testing data, and performance metrics. Chapter III also includes an empirical study, with exploratory data analysis, data preprocessing, application of different machine learning algorithms, feature importance analysis, results, and a subsequent discussion.

Chapter I | The Air Travel Industry

This chapter provides an overview of the air travel industry, highlighting its importance for the global economy and contributions to various sectors, followed by its characteristics such as market structure, competition, and net margins, ending with some of the challenges faced by airlines in their decision-making processes, comparing those challenges with the challenges they have faced in the last century.

1.1. Industry Importance

The quality, quantity, and diversity of goods and services that are currently offered have been changing throughout time, and this is the human face of economic development. "Economic growth represents the expansion of a country potential Gross Domestic Product (GDP) or national output" (Samuelson & Nordhaus, 2010, p. 502).

Economists who have examined economic growth have discovered that the driving force behind progress must rely on the same four components, regardless of a country wealth level. These four components, commonly referred to as factors of growth (Samuelson & Nordhaus, 2010), are summed up in Table 1.

Table 1 | Factors of growth of an economy and some examples of how to assess them.

Factors of growth	Means of growth
Human Resources	Labor supply Education Skills
Natural Resources	Environmental Quality Fuels
Capital	Roads Intellectual Property
Technological Change and innovation	Engineering Science Management

Adapted from: Samuelson and Nordhaus (2010)

These means of growth correspond to some ways in how we can assess the growth of an economy. For example, any factor that promotes employment, is indirectly promoting the growth of the economy.

The literature studying the impact of aviation in economic growth is still scarce. For instance, Irwin and Kasarda (1991) studied the impact of expanding the air travel network in metropolitan regions on economic output and found that a 10% boost in accessibility and centrality of urban aviation is correlated with a 4.29% rise in employment. In addition, Button and Taylor (2000) discovered that, for every 1000 air passengers transported, 1.5 jobs were created in industries reliant on the quality of local transportation services.

Many other authors found a positive relationship, some stronger than others, between the changes in air traffic, usually measured by the number of passengers and/or cargo carried by airlines, or the number of flights, and the effect on the economy (Blonigen & Cristea, 2015; Brueckner, 2003; Green, 2007; Marazzo et al., 2010; Sheard, 2014; Tveter, 2017). This relationship was found both in developed countries, as in developing countries (Gibbons & Wu, 2020).

Carbo and Graham (2020) go even further and argue that "there are incentives for policymakers around the world to invest in the aviation sector as the economic returns of these policies could have a significant magnitude" (p. 10). After all, the aviation industry makes a significant contribution to the global economy. According to some estimates, the contribution of aviation to the global economy is roughly equivalent to the entire GDP of the United Kingdom (International Civil Aviation Organization, 2019). This highlights the importance of the aviation sector in terms of economic activity and job creation.

Besides, air transport is considered to be a crucial element in overcoming distance and facilitating increased interactions and connections among people, businesses, and regions (International Civil Aviation Organization, 2019; Zhang & Graham, 2020).

Aviation plays a vital role in providing transportation for certain health and humanitarian aid needs. In many cases, air transport is the only feasible means of transportation for people and goods in remote or disaster-stricken areas. To illustrate this vital role, in emergency situations like natural disasters, war, or epidemics (e.g. COVID-19), aviation is used to transport medical supplies, personnel and patients (International Civil Aviation Organization, 2019).

Ensuring equal and inclusive access to education and promoting lifelong learning are critical for the growth and development of any society. The number of students who choose to study abroad has grown significantly, from 2.1 million in 2000 to 5.1 million in 2017. For many, studying abroad is crucial for accessing higher-quality education, and sometimes this means traveling to another part of the world. Without air transport, these opportunities would not be possible (International Civil Aviation Organization, 2019), or would be much harder.

Air transport plays a crucial role in enhancing the quality of life by expanding people's leisure and cultural experiences. Additionally, aviation also promotes cultural awareness and understanding. Traveling offers the opportunity to interact with different cultures and learn about their customs and way of life, thereby fostering a sense of unity and empathy among people (International Civil Aviation Organization, 2019).

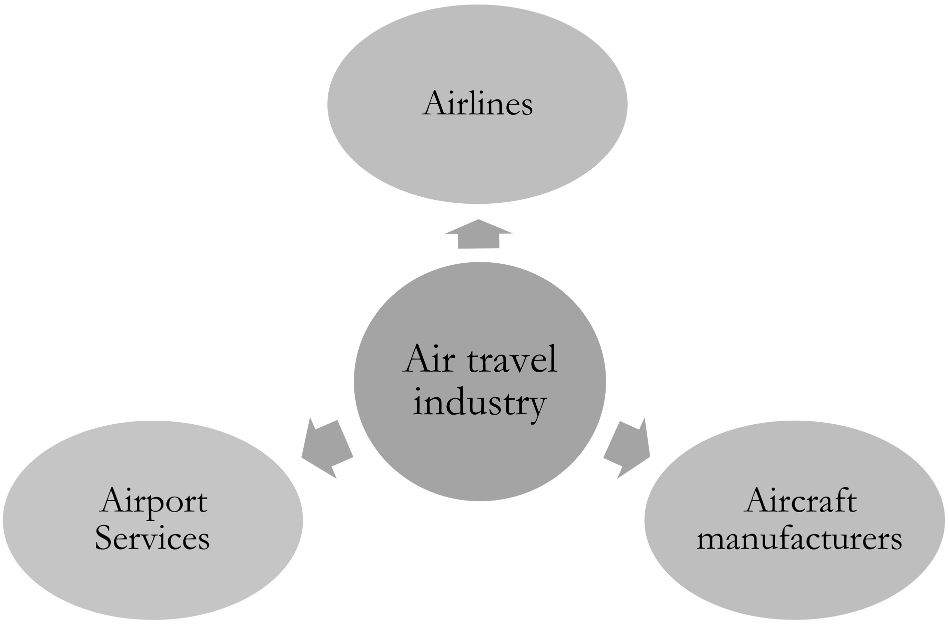
All in all, the significance of the airline industry is undeniable, as it provides a range of economic, health, humanitarian, and educational benefits. Besides understanding its importance, it is also relevant to characterize this industry.

1.2. Industry Characterization

This section begins by providing an overview of different companies that play a role in the air travel industry, even if not being airline companies, and afterwards narrows in on airlines as the main focus.

The Air travel industry is a complex one since it relies on the collaboration and interaction of different types of companies that directly or indirectly contribute to it. Figure 1 illustrates the different roles of some of these companies.

Figure 1 | Different types of companies that contribute to air travel.



Source: Author

The companies offering air transportation services are airlines. They are in charge of managing flights and transporting people and cargo between different airports around the planet. To guarantee that planes leave and arrive on schedule, deliver exceptional customer care to their passengers, and adjust their offer to the existing demand, while remaining profitable, airlines must handle complicated logistics and planning decision-making problems.

Aircraft manufacturers are crucial for the development of the sector, since they challenge the limits of innovation and technology by creating, developing, and designing aircrafts. They aim to produce modern and innovative aircrafts that are safer, more efficient, and offer better experiences for passengers and crew.

Nowadays, more than ever, sustainability is another top priority, and eco-friendly aircrafts with reduced emissions, less fuel consumption and negative environmental effects are being developed[2]. Additionally, research is being conducted on the usage of alternative fuels (Cabrera & De Sousa, 2022; Yusaf et al., 2022).

[2]For example, Airbus is developing several technologies to reduce carbon emissions from airplanes (https://www.airbus.com/en/innovation/low-carbon-aviation, May 2023)

Airports are essential to the air travel industry because they offer the facilities and services required for airplanes to operate efficiently and safely. They act as important transit hubs, connecting travelers to various locations throughout the globe. On the other hand, air traffic control staff monitor and manage aircraft movement in the air, which is essential to guarantee the safe operation of every flight (Belobaba et al., 2016; Vogel, 2019).

Companies that handle ground transportation offer necessary services such as refueling, luggage handling and check-in. They are responsible for making sure that aircrafts are prepared to take off securely and on time. A good passenger experience is also greatly influenced by these companies, who make sure that luggage is handled with care and that passengers are always informed[3].

All in all, to make air travel possible and connect people and goods around the world, different types of companies from the air travel industry collaborate in a complicated network. Each company's capacity to contribute and work together while bringing their own special talents and knowledge is fundamental to the industry long-term survival. The sector has significantly changed how people and goods are transported around the globe, creating new opportunities, and bringing people closer together than ever before.

To illustrate the importance of this network of companies, it is possible to consider a simple example about passenger satisfaction. All the passenger experience is directly influenced by all the companies in this network. When a passenger buys a ticket, his/ her expectations about the quality of the service are deposited exclusively on the airline. If a passenger has a bad experience on check-in or if his/ her luggage is lost, he/ she will not be angry at the handling company, but at the airline.

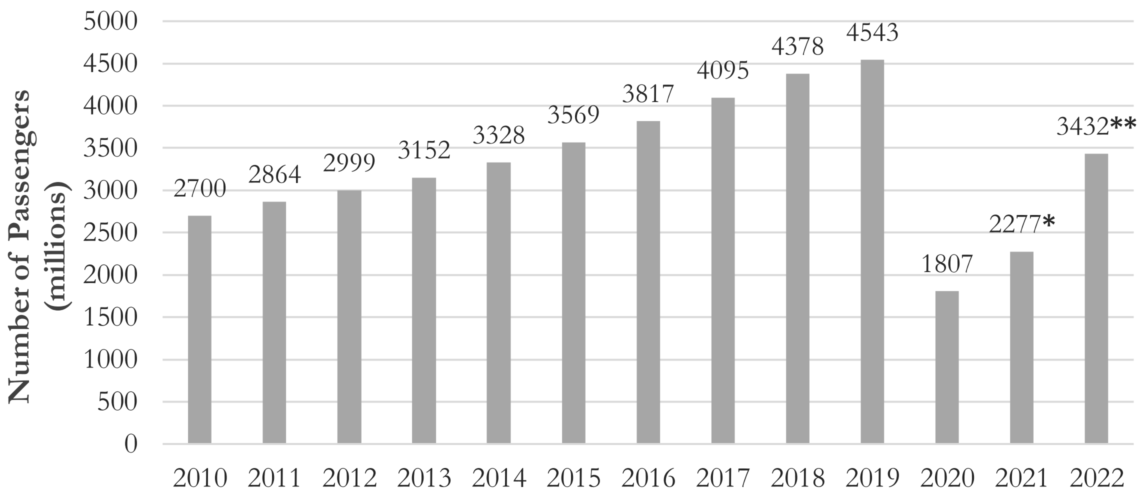
In 2019, TAP Air Portugal was the first airline in the world to receive the A330neo, a new airplane model manufactured by Airbus[4]. In the same year, a lot of complaints from the passengers travelling on that airplane model started to appear. Those were complaining of bad smells and nausea onboard. Later, Airbus admitted the existence of a technical failure

[3] https://www.groundforce.pt/en/ and https://www.portway.pt/en/ (May 2023)
[4] https://www.airbus.com/en/newsroom/press-releases/2018-11-airbus-delivers-first-a330-900-to-launch-operator-tap-air-portugal (May, 2023)

in those models[5]. Passengers who had all these bad experiences will resent the airline, and not the other companies. Thus, despite being inevitable to work with ground handlers and aircraft manufacturers, airlines must choose wisely the companies they partner with, because their main source of income satisfaction also depends on the performance of these other companies.

The number of passengers carried by airlines, present in Figure 2, has been increasing on average 6% per year, having increased approximately 68% in only 9 years. The year of 2020 was significantly affected by COVID-19, causing a drastic decrease of around 60% on the number of passengers carried, however the current forecasts refer that, in 2025, passenger numbers will correspond to 111% the numbers of 2019, the year before the pandemic started, increasing more for domestic than international flights (118% vs 101%) (*IATA*, 2022).

Figure 2 | Number of Passengers Carried globally from 2010 to 2022.



* Expected ** Forecasted

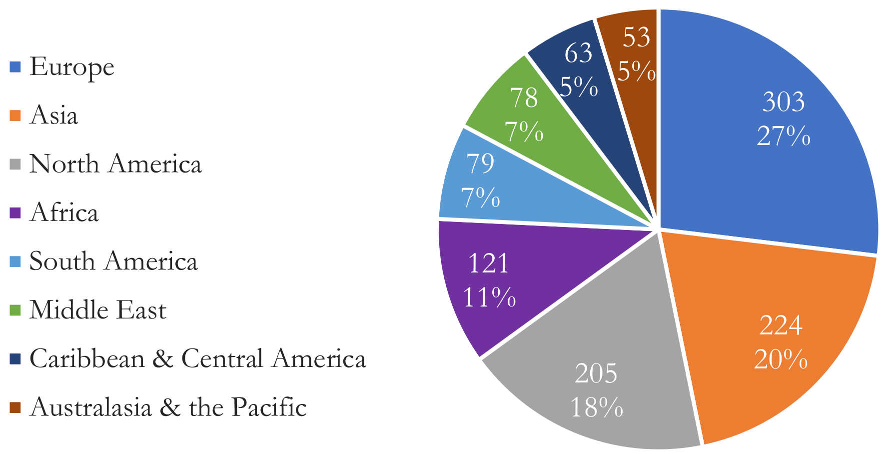
Source: Adapted from *Airline Industry Economic Performance* (2016, 2021)

There are hundreds of airlines operating across the globe, from large international carriers to regional airlines, making this sector a highly competitive one. Worldwide, according to IATA and ICAO, there are a total of 1126 commercial airlines, with Europe

[5] https://observador.pt/2019/07/15/airbus-admite-falha-tecnica-em-novos-avioes-da-tap-onde-tem-sido-registados-maus-cheiros-e-enjoos/ (May, 2023)

having the highest number, followed by Asia and North America, who have each approximately the same number, as per Figure 3.

Figure 3 | Number of Commercial Airlines per Continent



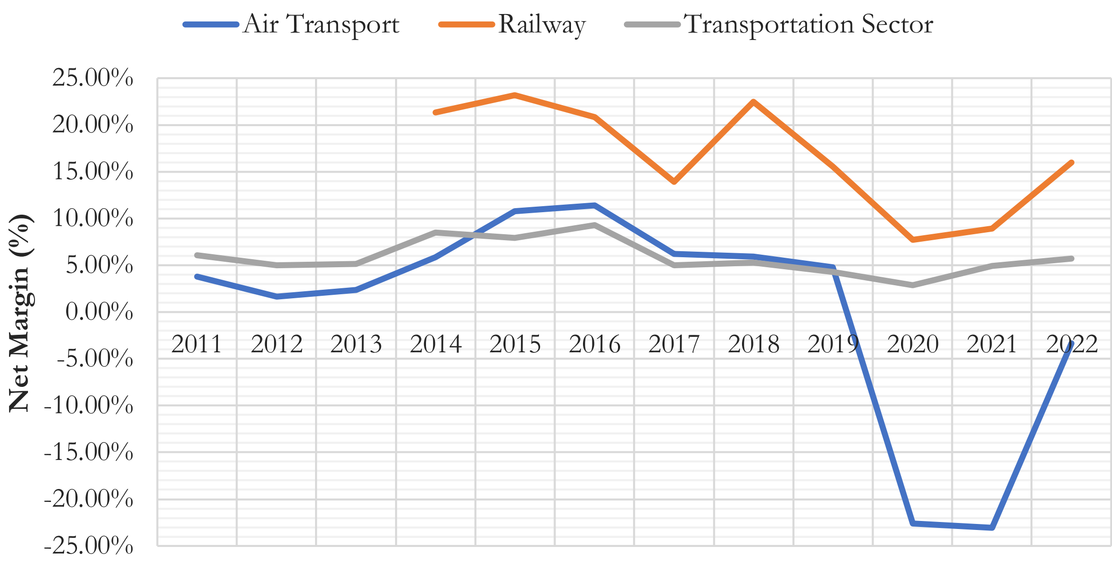
Source: Adapted from Jay (2023)

Over the last 12 years, as depicted in Figure 4, the air transport sector has had an average net margin of 0.31%, which is significantly lower than the transportation sector average of 5.83%. Moreover, the average net margin of railways was 16.66%, revealing a substantial difference between the profitability of these two modes of transportation.

However, when disregarding the years of COVID-19 (from 2020 to 2022), the average net margin on air transport is similar to the one of the whole sector: 5,86% vs 6,28%. Nevertheless, the difference of profitability to the railways remained significant. Thus, when considering both Figures 2 and 4, it is possible to verify that the airline sector was significantly affected by the COVID-19, more than the railway sector or the transportation sector, on average.

The data suggests that the airline sector may be more vulnerable to pandemics than any other modes of transportation. This is in line with the findings of Sun et al. (2020), who argues that the aviation sector was one of the economic sectors worst affected by COVID-19. Additionally, this pandemic was not an exception, since events like the SARS outbreak in 2003, the aviation influenza H5N1 in 2006 and the swine influenza H1N1 in 2009 also demonstrated the vulnerability of this sector to global infectious health threats (Chung, 2015; Epstein et al., 2007; Mason et al., 2005; Sadi & Henderson, 2000).

Figure 4 | Net margins of airlines, railways, and the transportation sector from 2011 to 2022



Source: Compiled from the datasets of Aswath Damodaran[6]

1.3. Airlines' Challenges and Decision-making problems

Commercial passenger air transport, in alternative to exclusive cargo air transport, has unique features that set it apart from other industries. Recent changes in this sector have been influenced not only by technological advancements, but also by legal and cultural changes. These changes, which have taken place over the past four decades, have had a significant impact on the industry structure, characteristics, and challenges.

Before the 1978 Airline Deregulation Act in the US[7], that completely liberalized its market, the industry was strictly regulated. It was usual for different states and/or countries to establish air service agreements (ASA), where the rules for the airline operation were determined. Even tough each ASA was different, they would always make reference to a set of four key elements (Belobaba et al., 2016), present in Table 2.

[6]Reputable Professor of Corporate Finance and Valuation, the datasets are available in https://pages.stern.nyu.edu/~adamodar/ (May, 2023) under *Cash Flow Estimation > Operating and Net Margins by Industry*.
[7]In EU, the liberalization of the air market started in 1986, with the Single European Act, and it was a decade-long process, with several rounds of regulatory measures being published (Debyser, 2022)

Table 2 | Four Key Elements in any Air Service Agreement

Key Element	Description	Example
1) Market Access	The possible city-pair connections that could be established between the states and/ or countries covered by the ASA were established.	If it was only determined a connection between New York and Lisbon, no airline could operate a flight between New York and Porto.
2) Airline Designation	Specific airlines were designated to operate the flights between two cities.	Between the USA and Portugal, the USA would determine that only Delta Airlines would operate a route established in 1), and Portugal would choose TAP Air Portugal. Other airlines wouldn't be able to operate the specified route.
3) Capacity	Both the frequency of flights, and the number of seats available in each flight, was fixed.	Flights operated by TAP between Lisbon and New York could only be allowed to operate 5 times per week (not more, not less), and each flight could only have a capacity for 150 seats.
4) Airfares	The fares to be charged were determined. However, they were subject to government approval.	Delta Airlines could not choose the price(s) to charge for its flight from New York to Lisbon. If the defined price was 900$, then the price to charge would be that one.

Source: Adapted from Belobaba et al. (2016)

With all these restrictions and regulations in place, the strategic, tactical, and operational decisions of every airline were somewhat limited.

On a strategic level, the capacity of airlines to grow their networks and compete with other airlines was constrained. Also, having this uncertainty about which routes it would be able to operate, and with which capacity, limited the airline decision on which airplanes to order. Actually, this is typically a long term decision, since "the average lifespan of a commercial aircraft spans from 20 to 30 years" (Ceruti et al., 2019, p. 520). Given the restrictions on airfares, airlines could not differentiate themselves using pricing strategies.

This made it challenging for airlines to gain a competitive edge and sustainably expand their companies and satisfy their passengers.

On a tactical level, it would be harder (if not impossible) to adjust the flight schedule to optimize crew utilization or to respond to demand changes – for example, if the airline noticed a demand change from Sundays to Mondays it would need to negotiate the change with the government or else it would still need to stick to Sundays. On an operational level if, for some reason, a flight had to be cancelled, and assuming the restrictions on capacity, it could be hard to find a way to transport the affected passengers to their destination.

Given all these limitations, even though competing with other airlines was not easy, it was still done, and it would usually "take the form of offering more service and/ or better amenities" (Moore, 1986, p. 1). For instance, with the objective of increasing passenger satisfaction, smoking inside the plane was not prohibited (as it is today), the seats used to be much more comfortable (with much more legroom and width), and even the food served was not compared to how it is today.

It was only after deregulation that cost efficiency, operational profitability, and competitive behavior have become the three main challenges facing airline management (Belobaba et al., 2016). This means that some of the challenges airline companies have to face are the same as before, but now they have more degrees of freedom considering the decisions that is up to them to make. They still have to provide a service that will satisfy their passengers, but this challenge, for instance, has become much harder, because now airlines have also to consider other concerns that can even be incompatible with each other.

As seen before, prior to deregulation, airlines were not allowed to compete on price. Therefore, they could focus on providing a high-quality service to their passengers, being able to offer free meals and drinks and provide comfortable seats, for example. However, after deregulation, airlines were free to compete on price. This means that they now must focus on cost efficiency to be competitive, having to reduce their costs to offer lower fares. This inevitably led airlines to cut back on services, such as meals and free drinks and comfortable seats, because these perks are incompatible with lower costs, leading passengers to be less satisfied with their service.

Airlines can now choose the markets and routes to operate, and even though these decisions are still subject to the approval of the regulator, this is usually only a formality, and not a restriction used to prevent market competition as before. This is a particularly difficult, but important, strategic decision, that requires a lot of thought. Additionally, airlines are free to operate the aircraft with the frequency they wish – only being limited by the airports capacity to receive the aircraft with the size they want to use and at the time they want.

Airlines can also charge the prices they want, having, however, to be careful about the prices their competitors are charging, and to consider the (price – demand) pair since higher prices offered will bring lower demand (Samuelson & Nordhaus, 2010). Usually, there are systems in place that continuously optimize the price to be charged – yield management systems (Ben-Yosef, 2005; Tretheway, 2011; Viglia & Abrate, 2020) – with the end goal to fill the plane and get the maximum revenue.

Also, the pricing decisions made by an airline should be faced as a strategical decision. Since the deregulation, the market has low-cost carriers available, which are airlines whose main objective is to lower operation costs and provide the lowest price possible to the passenger (Alderighi et al., 2012; Franke, 2004; O'Connell & Williams, 2005). Before airline deregulation in 1978, air travel was mainly for the wealthy, as it was a luxury that only a privileged few could afford. It was an exclusive and expensive mode of transportation, with roughly 75% of Americans having never flown by 1977, number that reduced to only 13% in 2020 (Andrew Follett, 2021).

All airlines encounter operational challenges, including bad weather, congestion at airports, and mechanical issues with the aircraft. These problems may make it difficult for airlines to operate their flight schedules as intended, which could lead to interruptions including flight cancellations and arrival and departure delays (Hassan et al., 2021). However, in case of aircraft maintenance, systems are being developed to use Artificial Intelligence (AI) to inform airlines in advance if a problem is likely to occur (Daily & Peterson, 2017; Stanton et al., 2023). As a result, these systems can save costs by reducing unscheduled maintenance, minimize flight disruptions, and improve passenger experience by reducing the frequency of unexpected maintenance-related delays.

The companies' operational performance is significantly impacted by these interruptions, which are relatively frequent in the aviation sector. Airlines must fix flight and crew schedules, and passenger itineraries to reduce the impact of these interruptions. As a result, disruptions may cause a significant increase in an airline operating costs, such as more crew working overtime, more fuel being used, compensating passengers for delays, or paying for new accommodations (Hassan et al., 2021).

Compared to other sectors or even industries, the airline sector is extremely costly. Buying, maintaining and disposing of each aircraft is extremely expensive (Mofokeng et al., 2020). Operating an aircraft is costly, with an average of around 25% of operating expenses being dedicated to paying fuel (Statista Research Department, 2023).

Recently, in an effort to reduce the sector's climate impact, the EU is to introduce minimum quotas on the use of Sustainable Aviation Fuel (SAF). This fuel can be mixed with the fuel currently in use, in different proportions, however it is even more expensive than the one currently used (Grimme, 2023; Zhang et al., 2020). So, airlines must manage the fine line between being sustainable and being profitable.

Even though the sector is less regulated than it was before, it is still heavily regulated. Nevertheless, the regulations currently in place are not only to guarantee the security of all operations, but also to protect the market from anti-competitive practices or to protect the rights of the passengers (Starkie, 2012). For instance, EU261 is a regulation that establishes air passenger rights and compensation for flights that were cancelled or delayed and departed from or arrived at the EU (*Air Passenger Rights*, n.d.; Ritorto & Fisher, 2017). Additionally, and for the case of Portugal, there is currently in place a regulation dictated by the National Civil Aviation Authority (NCAA[8]) imposing that every flight departing from Madeira Airport should be insecticide-treated[9].

Finally, one of the most important and difficult challenges airlines face is satisfying and retaining their passengers. The decisions airlines make to improve their service or strategy are fundamental, since the main revenue of an airline comes from ticket and ancillary sales. Ancillary sales are those sales that do not come from the sale of tickets. For example, they usually include paying for seat selection, for food onboard, for priority boarding, among others. If the passengers are not satisfied, and the airline does not have

[8]From the Portuguese ANAC – Autoridade Nacional da Aviação Civil.
[9]https://www.anac.pt/vPT/Generico/InformacaoAeronautica/CircularesInformacaoAeronautica/Documents/CIA_17_2021.pdf

mechanisms defined to address their dissatisfaction, they will eventually stop travelling with the airline, leading to a reduction of the financial performance of the company.

In this highly competitive industry, as seen in Figure 3, passengers have many available choices and are quick to switch to another airline if they feel their satisfaction or security is not a priority. It is essential for airlines to show a genuine dedication to meeting the needs of their passengers since losing customers can lead to serious repercussions for their business, and even strengthen their competitor's position.

Since 1970, the yield of carriers dropped about 50% (Doganis, 2002), meaning that, even though the number of passengers caried by airlines increased, and the industry itself grew, the revenues didn't accompany this growth. Airlines had to improve their efficiency by optimizing their air connections and managing their resources to remain competitive. Those that failed to do so were either merged with other companies or forced to declare bankruptcy (Fu et al., 2010).

For instance, Pan American World Airways, commonly known as Pan Am, was once considered one of the greatest airlines in the world. However, it faced significant challenges and ultimately failed to adapt to the changing environment of the aviation industry after the 1978 Airline Deregulation Act – which posed significant obstacles for established airlines. Pan Am struggled to compete with emerging carriers and faced difficulties in maintaining profitability. Pan Am was not alone in facing financial difficulties during this period. Other major airlines, such as Continental Airlines, Braniff, and Eastern, also filed for bankruptcy or faced significant challenges during the period (Singh & Joshi, 2022).

Chapter II | Air Service Quality and Satisfaction

As seen before, guaranteeing the quality of the service and the satisfaction of passengers is of utmost importance for every airline. Yet, to start the process of designing or improving their strategies – service and product characteristics –, airlines must start by understanding the passengers they are dealing with.

By understanding their passengers, airlines can focus on the aspects the passengers value and differentiate their service, which in turn will ensure a competitive advantage (Anderson et al., 1994). But first, it is important to establish how the concept of service quality – which is what airlines can control, in part – connects and influences passenger satisfaction.

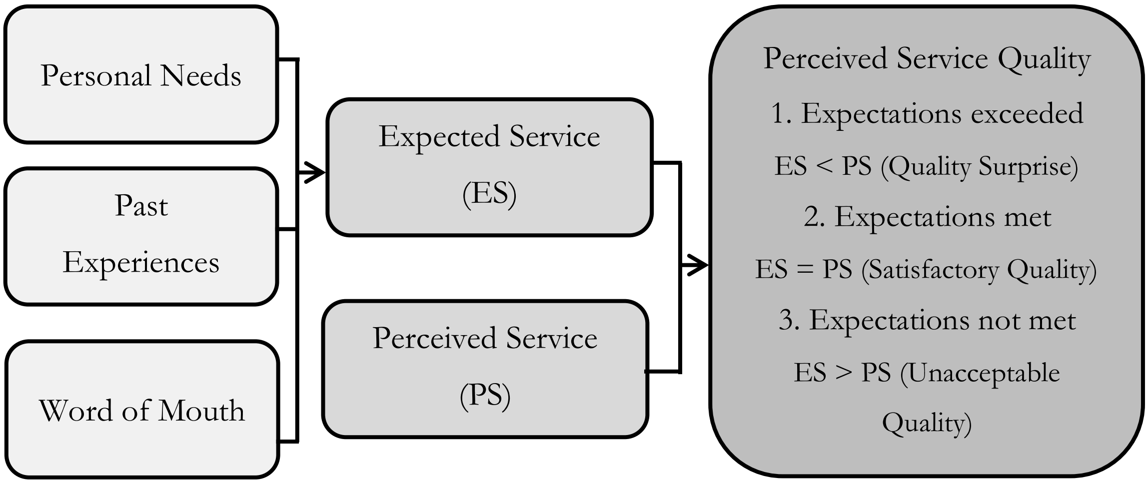
2.1. Service Quality and Passenger Satisfaction

Extensive research has been conducted on service quality and its measurement, with a particular focus on exploring the different concepts of service quality that are connected to customer attitudes and satisfaction (Taylor & Baker, 1994; Teas, 1993). Despite existing several definitions of service quality in the literature, there is a consensus that it represents the gap between the expectations and the perceptions of customers (Asubonteng et al., 1996; Uzunboylu, 2016; Wisniewski, 1996; Zahari et al., 2008).

In this dissertation, the perspective of Parasuraman et al. (1985) will be adopted, which argues that service quality results from the "comparison of consumer expectations with actual service performance" (p. 42), originating the Perceived Service Quality. The same authors proposed a Service Quality Model, adapted in Figure 5, defending that the perceived service quality depends on the Expected Service and the Perceived Service. The Expected service, on its turn, depends on Personal Needs, Past Experiences and Word of Mouth.

Word of mouth can be defined as the exchange of marketing information between consumers, which has a fundamental role in shaping their behavior and changing attitudes towards products and services (Katz and Lazarsfeld, 1966 as cited in Huete-Alcocer, 2017). It tends to be very persuasive and, as a result, exceptionally effective (Bristor, 1990 as cited in Bansal & Voyer, 2000), primarily because consumers often depend on informal or personal communication sources over formal or organizational sources, like advertising campaigns, when making purchase decisions (Bansal & Voyer, 2000).

Figure 5 | Service Quality Model



Source: Adapted from Fitzsimmons and Fitzsimmons (2006) and Parasuraman et al. (1985)

Between the years of 2017 and 2019, the distribution of passengers by age remained quite heterogeneous, with the age intervals between 25-34, 35-44 and 45-54 accounting for 23% each of total age groups of travelers, followed by the 55-64 years interval with 16% (Jay, 2023). This represents sensibly an equal distribution across different generations, making it challenging for airlines to understand what services their customers are expecting and adjust the perceived service accordingly to meet their needs.

The reason behind this difficulty is related to the fact that "each generation has unique expectations, experiences, generational history, lifestyles, values, and demographics" (Williams & Page, 2011, as cited in Chaney et al., 2017, p. 185) that influence their buying behaviors. Additionally, other authors found that passengers' perception of international air travel service quality can vary depending on factors such as age, gender, income, occupation, and marital status (Clemes & Choong, 2008). Every flight will inevitably contain passengers with very different demographic profiles, each with different expectations, perceptions and needs. Thus, the objective is not to satisfy every passenger – that would be impossible –, but to try to find a common ground between such different profiles.

In relation to Perceived Service, Kim and Lee (2011) resort to the SERVQUAL[10] model, developed by Parasuraman et al. (1988), to point out five dimensions of perceived

[10] SERVQUAL, or Service Quality, is a model used to determine the differences between customer expectations and perceptions regarding a certain product or service (Parasuraman et al., 1988).

service quality in the airline industry. A brief definition of each of the five dimensions, as well as the way they apply to the airline industry, is in Table 3.

Table 3 | Dimensions of SERVQUAL and application to the airline industry.

Dimension	Definition	Application to the Airline Industry
Tangibles	Measures the physical appearance of the service, including the facilities, equipment, and appearance of personnel.	Seating comfort, seating space and legroom, inflight entertainment (e.g., Magazines), employee appearance and meal service
Reliability	Measures the ability of the service provider to provide a reliable and dependable service, including the ability to perform the service as promised and the ability to provide the service consistently.	Punctuality, efficiency of the check-in process, convenience and accuracy of reservations and ticketing, on-time departures and arrivals
Responsiveness	Measures the willingness of the service provider to help and provide prompt service to customers	Solve service problems (flight cancellation, baggage loss, other complaints), response to emergency situations, prompt baggage delivery
Assurance	Measures the knowledge, courtesy, and ability of service providers to inspire confidence and trust in their customers.	Show courtesy towards passengers, knowledge to answer questions and ensure safety onboard, airline's reputation
Empathy	Measures the ability of service providers to demonstrate a caring and individualized attention to customers' needs. It involves understanding the customer's situation[11].	Providing the seat a passenger prefers or meals through a pre-order system, having a Frequent Flying Program, flexible travel options

Source: Adapted from Kim and Lee (2011) and Parasuraman et al. (1988)

[11] LCA are known for not refunding tickets under any circumstance. However, easyJet is an example of a LCA that allows full refunds in case of family loss (https://www.easyjet.com/en/terms-and-conditions, point 5.3.2), showing that they care for their passengers in such complicated moments of their lives.

According to Parasuraman et al. (1988), satisfaction corresponds to a customer's pleasurable level of fulfilment, distinguishing it from service quality as customers perceiving the former as a long-run overall judgment of service delivery, and satisfaction as a judgement that is specific to each transaction. Oliver (2014) adds that satisfaction refers to the evaluation of whether a product or service feature, or the product or service as a whole, is providing a satisfactory level of fulfilment in relation to consumption, which may include both over- and under-fulfilment.

There is a major debate in the literature about the relationship between perceived service quality and customer satisfaction. For that effect, three models are considered: independent-effects model, customer satisfaction to perceived service quality and perceived service quality to customer satisfaction (Dabholkar et al., 2000).

The latter model is widely accepted, with some authors suggesting that, to achieve a high level of customer satisfaction, the service provider should deliver a high level of service quality, resulting in service quality as an antecedent of customer satisfaction (Anderson et al., 1994; Brady & Cronin, 2001; Cronin et al., 2000; Kim & Lee, 2011). Nevertheless, some other authors found the two constructs independent, but strongly correlated, meaning that an increase in one would likely increase the other (Sureshchandar et al., 2002).

Cronin and Taylor (1992) found that service quality is an antecedent of consumer satisfaction, but that consumer satisfaction exerts a more robust effect on purchase intentions than service quality. Therefore, managers should emphasize customer satisfaction programs instead of focusing only on service quality. This is because factors such as convenience, availability and price can enhance satisfaction even if the service quality is not the highest and it may not necessarily affect consumers' perceptions of service quality (Cronin & Taylor, 1992). LCA are an example of this. They may prioritize factors such as price and convenience (e.g., direct routes between secondary airports, while FSA [Full-Service Airlines] may force a layover in their hub) over traditional measures of service quality to enhance customer satisfaction and increase purchase intentions.

This dissertation will adopt the perspective that higher service quality translates into customer satisfaction. Even tough Cronin and Taylor (1992) point is valid, considering that service quality is ultimately a subjective concept, it can be assumed that factors such as price and convenience are already taken into account by passengers when they assess service quality.

2.2. Airline Quality and Satisfaction Dimensions

Literature shows that the relationship between passengers and airlines is influenced by several factors, among which service quality is determinant for longevity. Passengers often consider the quality of the service provided by airlines when selecting one for their travel (Truitt & Haynes, 1994). However, there may be a discrepancy between the quality of service perceived by passengers and the quality measured by airlines (Tsaur et al., 2002). This suggests that airlines may need to pay more attention to the passenger experience and work towards aligning their perception of quality with the one of their passengers in order to promote long-term relationships.

In the airline industry, what defines quality varies according to several studies. In this industry, which is strongly oriented to services, the decisions about the relevant drivers to increase passenger satisfaction is of utmost importance and requires a precise knowledge of its key antecedents from a customer's point of view (Höck et al., 2010 as cited in Ringle et al., 2011). Table 4 presents an overview of some dimensions studied by different authors. Then, the next subsections examine some dimensions in greater detail.

Table 4 | Some Service Dimensions that define quality and satisfaction.

Authors	Dimensions / Drivers
Elliott & Roach (1993)	Punctuality, baggage handling, food and drinks quality, seat comfort, in-flight service and check-in process
Truitt and Haynes (1994)	Check-in process, baggage handling, seat comfort, food and drinks quality, punctuality
Chang and Yeh (2002)	On-board comfort, airline employees, reliability and convenience of service, handling abnormal conditions
Gilbert and Wong (2003)	Safety, Frequent Flying Program, Crew sympathy
Park et al. (2006)	On-board service, price, customer service, seating comfort, inflight entertainment, meal service, check in service

Rhoades and Waguespack (2008)	Punctuality, overbooking events, lost baggage, customer complaints

Source: Author's compilation

The next subsections present some of the several factors that may influence – or not – the satisfaction of a passenger. Since the main goal is to identify which dimensions of service attract customers to a specific airline, these subsections are based on literature about customer satisfaction and factors that passengers consider when choosing an airline to travel with. Also, in the last subsection, Socio-Demographic Characteristics, some of the factors explored in earlier sections are presented again, this time linked to socio-demographic factors.

2.2.1. Reservation Channels

A reservation channel refers to the different ways passengers can book their flights, such as through a travel agency, the airline's website, or through a mobile app. Reservation channels convenience is important for air passengers' satisfaction because it allows them to make reservations in a way that is most convenient for them. The convenience of reservation channels is particularly important because it allows passengers to easily compare prices and flight schedules, to book flights quickly and even manage their reservations, especially when online channels are considered (Harcar et al., 2012).

Booking convenience can be improved by offering multiple reservation channels and ensuring they are user-friendly, accessible, and secure, which can increase passenger satisfaction. Additionally, providing support and assistance to passengers who encounter problems with their reservation can also help to improve their overall experience. Furthermore, as more customers turn to online reservation channels, airlines can reduce costs associated with manual booking processes, leading to improved operational efficiency (Bitner et al., 2002; Hanke & Teo, 2003; Meuter et al., 2003).

Overall, the literature agrees that several aspects of reservation channels contribute to passenger satisfaction and airline choice and loyalty. For instance, Singaravelu and Amuthanayaki (2017) reveal that passengers value online ticket booking, namely the possibility of checking in for their flights and booking seats online, whereas Ong and Tan (2010) found that the booking methods were a good predictor of airline carrier choice.

The convenience of purchasing air tickets was considered to be an important selection attribute for LCA, in comparison to FSA (Kim & Park, 2017). Inclusively, it was considered the third most important factor when selecting an airline, with online and ease of booking being mentioned (Kurtulmuşoğlu et al., 2016). Additionally, the majority of customers would not sacrifice the possibility to book tickets online even if it meant that the price of the ticket would be lower (Campbell & Vigar-Ellis, 2012).

The channels used for booking play a crucial role in determining both the adoption duration of LCA and the level of loyalty. Passengers who value a more convenient ticket booking process are likely to adopt LCA sooner and show stronger loyalty. To increase the probability of adoption and earn stronger loyalty, LCA can upgrade their booking channels by improving their ease of use and functionality. Offering advantages to passengers using internet booking can also help LCA in achieving their goal (Chang & Hung, 2013).

Teichert et al. (2008) identified three airline passengers' segment profiles: comfort, efficiency and price. For the efficiency profile, composed mainly by business travelers who flew frequently due to business reasons, it was really important the easiness of booking a ticket and the flexible and convenient way companies made possible to change the ticket.

On the other hand, despite the convenience of the ticketing process being one of the most important dimensions for passenger satisfaction, Chou et al. (2011) found that the quality of the reservation services was one of the least important dimensions.

2.2.2. Flight Conditions

Understanding the importance of flight conditions for passenger satisfaction, such as convenience of schedules and frequency of flights, is crucial in the airline industry. Convenient and reliable schedules that are aligned with passengers' needs and offer sufficient flight frequency can improve satisfaction by providing flexibility and convenience.

For example, passengers who are travelling for tourism may want a flight that departs in the morning, so that they have the option to spend more time in the destination. The same applies on return where they might want a flight that departs at night. Also, if an airline only flies a certain route twice a week, passengers are somewhat conditioned on the number of days they can spend at the destination.

In contrast, inconvenient schedules or infrequent flights can lead to frustration, decreasing passenger satisfaction. By studying this relationship, airlines can make informed decisions and improvements to enhance customer experiences and loyalty.

Compared to flight scheduling, few authors studied flight frequency. Wen and Lai (2010) argue that flight frequency was positively related with the probability of an airline being chosen, with Business Travelers having higher expectations about having more flights to choose from (Gilbert & Wong, 2003). For instance, in the case of business travel, many people may have a preference to return home the next day. However, if an airline operates the route only twice a week, it can make it impractical or even impossible to satisfy such preferences. On the other side, some authors found a positive link, however it was not statistically significant (Chang & Sun, 2012).

Overall, the literature agrees that Flight Schedule is important for passenger satisfaction and it is one of the factors considered when choosing an airline. Saha and Theingi (2009) hypothesized that the flight schedules of airlines positively influences passengers satisfaction. They found a statistically significant strong correlation between the convenience of flight schedules and satisfaction, proving their hypothesis.

For passengers traveling for business purposes, it was found that they are more likely to consider Flight Schedules when choosing an airline to travel with (Milioti et al., 2015). Additionally, when comparing FSA and LCA, Flight Schedules was considered to be one of the most important reasons for choosing a FSA to travel with, while the primary reason for choosing a LCA was, by far, the price of the ticket (Kim & Park, 2017; O'Connell & Williams, 2005). In relation to the class the passenger is traveling in, there was no distinction between economy and business class passengers, with the Flight Schedule contributing equally to both (Teichert et al., 2008).

Basfirinci and Mitra (2015) found that acceptable flight schedules and enough flight frequencies was seen as an attractive attribute. This means that when these attributes were present, they would lead to high levels of satisfaction, but if they were not present, the passengers would not be dissatisfied. The reason for this is that passengers would not typically be expecting for convenient flight schedules or enough flight frequencies. All in all, both of these attributes are sufficient but not necessary for passenger satisfaction (Busacca & Padula, 2005)

Tahanisaz and Shokuhyar (2020) analyzed 10 clusters of passengers (based on flight intention, class and frequency of flights). For all the clusters, contrarily to Basfirinci and Mitra (2015), the absence of convenient flight schedules would cause dissatisfaction to passengers. However, for half the clusters, having convenient flight schedules would bring satisfaction, whereas for the other half, it would not add satisfaction. Some other authors, however, considered this factor to be the least important one (Chou et al., 2011).

2.2.3. Inflight Service

Understanding the potential impact of inflight services such as food and beverages, entertainment options, and the helpfulness and friendliness of cabin crew on passenger satisfaction is important in the airline industry. It is likely that these factors contribute to passengers' overall flight experience and may have an influence on their satisfaction levels.

Overall, there is consensus amongst various authors in the literature regarding the significance of cabin crew in relation to passenger satisfaction and airline selection. Generally, passengers are satisfied with the friendliness, helpfulness and professionalism of cabin crew (Farzadnia & Vanani, 2022), being one of the key factors for those traveling in economy class (Sezgen et al., 2019).

Other studies also identified the cabin crew characteristics – mentioned above – as the most relevant dimension for airline choice (Lucini et al., 2020; Milioti et al., 2015; Wen & Lai, 2010). Additionally, for Saha and Theingi (2009), it was the third most important service quality dimension tested, whereas for Shen and Yahya (2021) it was the first.

Amongst Turkish travelers (in comparison to US travelers), competent cabin staff at answering customers' questions and meeting their needs was considered a must-be requirement. This means that if this requirement was not present, passengers would be dissatisfied. However, if present, it would not bring additional satisfaction (Basfirinci & Mitra, 2015). Similar results were found by Tahanisaz and Shokuhyar (2020), but regarding cabin crew courtesy. Nevertheless, Chou et al. (2011) found that courtesy was one of the most important factors for service quality.

Tsafarakis et al. (2018) and Lucini et al. (2020) defend the importance of inflight entertainment. The former argued that it is one of the most important factors affecting passenger satisfaction, whereas the latter defends its relative significance, being half the importance the same author found for cabin crew. For Alamdari (1999), even though the inflight entertainment was not one of the most relevant factors for choosing an airline, it contributed significantly for passengers' satisfaction with the airline.

For Tahanisaz and Shokuhyar (2020), the absence of inflight entertainment would cause dissatisfaction amongst passengers, however there are different results (depending on passenger clusters) considering whether the presence of it would bring satisfaction or not. Other authors argue that it is the least important factor for service quality and airline choice (Chou et al., 2011; Milioti et al., 2015).

Food and Drinks (if included) have a positive influence in satisfaction for both economy and business passengers (Teichert et al., 2008), being important for it (Lucini et al., 2020; Tsafarakis et al., 2018). On the other hand, some authors also found that for the majority of the passengers, the presence and quality of different food and drink options would not add any satisfaction, but the lack of it would be a cause for dissatisfaction (Tahanisaz & Shokuhyar, 2020).

2.2.4. Cabin Facilities

Cabin facilities, including cleanliness and seating comfort, are essential for passenger satisfaction. A clean cabin creates a pleasant environment, while comfortable seating enhances physical comfort. These factors contribute to a positive flight experience and influence passengers' decision to choose an airline. Ensuring cleanliness and comfortable seating is crucial in meeting passenger expectations and promoting satisfaction.

In general, literature agrees that seat comfort is important for passenger satisfaction (Lucini et al., 2020; Tsafarakis et al., 2018) and for the perception of service quality (Chou et al., 2011; Shen & Yahya, 2021; Singaravelu & Amuthanayaki, 2017). For Kim and Park (2017), it was considered to be an important selection attribute on FSA, whereas for Wen and Lai (2010) it has a positive influence on all types of airlines, being one of the most important factors for airline choice.

The results of Kim and Park (2017) are expected, since considering that FSA typically have average prices higher than LCA, passengers may expect better comfort in exchange of the higher price paid. This is consistent with the findings of Campbell and Vigar-Ellis (2012), where the great majority of passengers would sacrifice legroom and onboard space for lower prices. Additionally, it is important to note that the seat, the legroom and the space inside the plane were found to be sources of major discomfort during air travel (Greghi et al., 2013), both for economy and business class passengers (Sezgen et al., 2019).

For both cleanliness and seat comfort, Tahanisaz and Shokuhyar (2020) found that it would not lead to more satisfaction, however, if these factors were not present, the passengers would be dissatisfied. Similar results were found by Basfirinci and Mitra (2015) for aircraft cleanliness. Nonetheless, some authors defend that the cleanliness contribute to passenger satisfaction and service quality (Chou et al., 2011; Shen & Yahya, 2021; Tsafarakis et al., 2018).

2.2.5. Ground Services

Efficient ground services, like baggage handling (this usually means the luggage that is checked and is transported in the airplane hold), play a crucial role in satisfying passengers. Correct baggage handling ensures passenger's belongings arrive safely to the destination, avoiding any inconvenience and frustration that may occur when the bags are lost or damaged. These factors contribute to passengers feeling secure and at ease, influencing their satisfaction.

It is important to note that these services are typically outsourced to external companies, which poses a challenge for airlines in terms of maintaining control over them. However, this is an aspect that should not be neglected by airlines, since ground staff contributes to overall passenger satisfaction (Saha & Theingi, 2009). It also does not help that both passengers traveling in economy class and business class do not have a positive idea of this staff (Teichert et al., 2008). The ground staff include the personnel at the check-in counter, at the boarding gates scanning the boarding passes, people handling the luggage from the terminal to the aircraft and vice-versa, among others.

As expected, luggage handling is an important factor for passenger satisfaction (Tsafarakis et al., 2018), being more valued by passengers traveling in economy class (Lucini et al., 2020). Nevertheless, both for passengers traveling in economy and in business class, disruptions in luggage handling was one of the main reasons for passenger dissatisfaction (Sezgen et al., 2019).

Loosing luggage was also considered to be one of the main reasons for difficulty and discomfort at the airport (Greghi et al., 2013). This is plausible because this is not a frequent problem for a single passenger, so when it happens passengers may feel lost on how to proceed, not to mention the obvious feeling of losing their belongings and not knowing if they will ever get them back. In these situations, airlines should provide clear instructions, and even compensate the passenger.

Chow (2015) used customer complaints as a proxy for passenger satisfaction. In a time frame of almost 10 years, baggage problems were the second biggest cause of complaints. Additionally, Basfirinci and Mitra (2015) found that for attributes like prompt and accurate luggage delivery and accurate handling of lost luggage, if those attributes were not adequate, passengers would be dissatisfied. However, if present, it would not lead to additional satisfaction.

2.2.6. Airline Operation

Punctuality and safety are crucial aspects of airline operations that significantly impact passenger satisfaction. Punctuality is essential for passengers who rely on airlines to reach their destinations on time. Delays and disruptions can lead to inconvenience, missed connections, and disruptions to passengers' plans, resulting in frustration and dissatisfaction.

On the other hand, safety is crucial as passengers trust their lives to airlines during their travels. A strong safety record and rigorous safety protocols promotes confidence and peace of mind to passengers, contributing to their overall satisfaction. Knowing that an airline prioritizes punctuality and maintains high safety standards creates a positive perception and enhances passengers' trust in the airline, ultimately leading to a more satisfying travel experience.

The degree of passengers' overall satisfaction is significantly influenced by their perceived safety, with a lower perceived risk generally leading to higher satisfaction (Johnson et al., 2006; Ringle et al., 2011). This level of perceived risk also has an impact on passenger behavior, as exemplified by the decline in passenger numbers following the September 11, 2001 attacks in the USA[12] (Siomkos, 2000).

Additionally, the relationship between perceived safety and satisfaction is strongly mediated by the purpose of travel, having a significantly greater influence on the satisfaction of passengers travelling for leisure purposes, compared to passengers travelling for business. This suggests that airlines, when advertising to leisure travelers, should emphasize safety features (Ringle et al., 2011).

The punctuality of an airline has a positive influence on its choice by passengers (Wen & Lai, 2010), being the second most important factor only behind the price of the ticket (Kurtulmuşoğlu et al., 2016), both for passengers traveling in economy and in business class (Teichert et al., 2008). While some authors found that it increases passenger satisfaction (Tsafarakis et al., 2018), others argue that an airline being punctual does not lead to satisfaction, and that passengers will only be dissatisfied if there are delays (Tahanisaz & Shokuhyar, 2020).

Nevertheless, punctuality is one of the most relevant drivers of service quality (Chou et al., 2011), and the lack of it is one of the main sources of difficulty and discomfort at the airport (Greghi et al., 2013). Using complaints as a proxy for customer satisfaction, Chow (2015) shows that flight delays accounts for half of the complaints made by passengers.

Song et al. (2020) used text mining to perform sentiment analysis in almost 25.000 reviews online. They showed that there is a significant and negative correlation between the user's emotions and their flight delays experiences. Since some delays are unavoidable and out of the airlines control – like the ones caused by bad weather conditions and strike by air traffic controllers – airlines should put more effort into properly assisting and informing their customers if these events come to occur.

2.2.7. Frequent Flyer Programs

Passenger loyalty, as in many industries, can be seen as synonymous of satisfaction with the service and product provided by the airline. This is one of the ways that makes an airline more competitive by retaining passengers who choose it not just once, but repeatedly.

[12] The 2001 attacks were coordinated terrorist acts by al-Qaeda, which involved the hijacking of airplanes that were used to crash into the World Trade Center towers in New York City.

Additionally, loyal passengers are less price-sensitive and more receptive to communication, making them highly attractive to the airline (Gómez et al., 2006).

Airlines use Frequent Flyer Programs (FFP) to build customer loyalty and to recognize it. By creating FFPs, airlines aim to differentiate themselves and stay competitive in relation to their competitors (Proussaloglou & Koppelman, 1999). These programs provide invaluable insights into passengers and their profiles and preferences. This way, the airline can craft its strategy towards fulfilling the requirements and preferences of its passengers (Maalouf & Mansour, 2007).

FFP membership represents a positive and highly significant influence on travelers' choice for an airline (Proussaloglou & Koppelman, 1995), being one of the main criteria for choosing a FSA over a LCA (Kim & Park, 2017; O'Connell & Williams, 2005). Nevertheless, some authors argue that it is the least important factor (Milioti et al., 2015).

Additionally, it has both direct and indirect effects over passenger satisfaction (Park, 2010). Chang and Hung (2013) argue that FFP can increase passenger loyalty towards LCA. This is particularly difficult to understand since the main objective of LCA is offering the lowest prices possible. Therefore, the type of passenger it usually attracts is the one who is always looking for the cheapest way of getting to the place it needs to, so, if a competitor offers a lower price, that passenger will not have any problem switching to another airline. This is in line with the findings of Campbell and Vigar-Ellis (2012), where the great majority of passengers would trade FFP for lower prices – this is why the majority of LCA do not have a FFP: they focus on offering lower prices than their competitors.

2.2.8. Socio-Demographic Characteristics

Understanding the impact of socio-demographic characteristics on passenger satisfaction is crucial for improving the overall customer experience. Different demographic groups have unique preferences, priorities, and expectations when it comes to their travel experiences. For instance, age can significantly influence the importance placed in service aspects such as seat comfort, entertainment options, or food quality. Income levels may also play a role in determining the value customers place on luxury amenities or cost-effectiveness.

By considering these socio-demographic factors, airlines can adjust their services and offerings to better meet the diverse needs and preferences of their passengers, or even adjust their marketing campaigns. This personalized approach can result in higher levels of customer satisfaction, loyalty, and ultimately, a competitive advantage in the industry.

Oyewole (2001) investigated whether demographic variables would influence passenger satisfaction in the same way they influence other aspects of consumer behavior. The author found that while household income and age had no visible influence on satisfaction, variables like education, marital status, gender and occupation did exert considerable influence on passenger satisfaction with airline services.

Regarding airline choice criteria, Milioti et al. (2015) reported substantial differences amongst passengers of different age, gender and nationality. Considering gender, males were found to be more likely to pay more attention to the size of the airline and the staff service, but to give less attention to safety, reliability and the price of the ticket, with this last aspect being more valued by females (Medina-Muñoz et al., 2018).

With respect to age, passengers in the 18 to 35 age group were less likely to find safety and reliability relevant, whereas customers over 35 years old considered flight schedule an important attribute. Taking into account nationality, in a survey made in the Athens Airport where Greek passengers represented 75% of the sample, the Greek passengers were found to put more emphasis on ticket price and staff service (Milioti et al., 2015). When considering Taiwanese and Chinese passengers surveyed in a proportion of 9:11, it was found that the former had greater preference for travel availability, ticket price and inflight service compared to the latter (Chen & Chao, 2015).

With respect to marital status, passengers married or living with a partner were found to prefer flight schedules, connections and inflight space, compared to singles not living with a partner. This last group showed less preference for catering (food and drinks) and entertainment, compared to married passengers. People with financially dependent children attached more importance to aspects like safety, punctuality, flight schedule and ticket price. Large families, for instance, showed preference for entertainment and catering (Medina-Muñoz et al., 2018).

Contrarily to Milioti et al. (2015), Medina-Muñoz et al. (2018) could not associate the age to the importance passengers gave to airline attributes. One possible explanation was that in each age gap, there was a great variety of passengers in terms of the other remaining socio-economic characteristics. Finally, regarding income, individuals with higher income prioritized ground service and travel availability, while those with lower income exhibited a higher sensitivity to ticket price, as expected (Chen & Chao, 2015).

2.3. Summary

It is evident from the literature that determining the importance of different dimensions for passenger satisfaction is a complex task. While some articles strongly argue for the significance of certain dimensions, such as flight frequency or luggage handling, others present contrasting viewpoints, suggesting that these factors may not have the same level of importance for all passengers. The different perspectives highlight the need for a detailed understanding of passenger preferences and the recognition that individual differences, situational factors, and cultural influences may significantly impact the perceived importance of different dimensions.

Therefore, it is fundamental to recognize that generalizations are rarely true and that tailoring strategies to meet the specific needs and expectations of diverse passenger segments is essential for achieving high levels of overall satisfaction. Each airline should understand its own passenger base and adjust its strategies accordingly to meet the unique needs and expectations of the passengers it serves.

Price was not included as one of the dimensions considered in this revision due to its strategic nature, as it represents a long-term decision that completely influences an airline's positioning and competitive strategy, rather than being a direct determinant of passenger satisfaction in the context of specific service dimensions. Also, airlines nowadays are using revenue management systems, with the consequence of each passenger paying a different price for the ticket. Therefore, it is possible that two passengers who are sitting near each other paid substantially different prices (for example, one passenger may have paid 50 euros, and the passenger next to him/ her paid 200 euros), while still receiving the same service quality.

The objective of this dissertation is not to motivate a complete restructuring of the airlines' positioning. Nevertheless, price was considered a significant factor in a great part of the reviewed articles, sometimes being considered the most relevant factor. For instance, "the pricing strategy (…) for the current and potential customers is (…) more effective than improving flight schedule, on-time performance, and frequency of flights." (Wen & Lai, 2010, p. 220)

In conclusion, it is clear that there are no possible generalizations in terms of which dimensions will lead to satisfaction or not. One of the potential problems in the great majority of the articles reviewed, is that they try to isolate each dimension and associate it with satisfaction or dissatisfaction. While this is an interesting approach, it represents a problem because the satisfaction of a passenger, or actually the satisfaction of any customer in any business, is not a single-variable function, but a multi-variable one, with different weights for each variable. In a scenario where a passenger experiences a punctual flight with large legroom, comfortable seating, and delicious food, but must deal with lost luggage, how can it be predicted whether the passenger was satisfied with the overall flight experience or not?

Chapter III | Predicting Air Passenger Satisfaction

Predicting passenger satisfaction is important for airlines as it enables them to proactively address and meet customer expectations. By accurately predicting their passengers' satisfaction levels, airlines can identify areas of improvement, adjust their services to improve the overall passenger experience and, eventually, get in touch with the customer to amend themselves. This proactive approach helps building customer loyalty, making customers choose the same airline again, and gaining a competitive edge in the industry.

Additionally, predicting passenger satisfaction allows airlines to allocate their resources effectively, optimize operations, and prioritize investments in areas that will have the greatest impact on customer satisfaction. All in all, understanding and predicting passenger satisfaction allows airlines to deliver a great service and build positive customer relationships.

3.1. Sources of Information

To effectively predict passenger satisfaction, it is important to first explore the different ways airlines gather information. This section examines some of the various approaches used by airlines to collect data about their passengers' experience.

Airlines can assess their passenger satisfaction through multiple ways and collect data to do so in more than one way. Passenger satisfaction levels can be determined by monitoring and examining consumer evaluations and ratings on websites like social media – for example, Twitter (Kumar & Zymbler, 2019; Misopoulos et al., 2014) – and review websites – like TripAdvisor or SKYTRAX (Brochado et al., 2019; Jain et al., 2019; Song et al., 2020).

TripAdvisor is an online platform known for its user-generated reviews and ratings, offering valuable insights into various aspects of travel, including hotels, restaurants attractions and airlines. Travelers many times rely on TripAdvisor to make informed decisions about airlines based on customer feedback and experiences shared by other users. Airlines can also use TripAdvisor reviews to assess passenger satisfaction and improve their services accordingly.

Figure 6 shows an overview of the overall review for easyJet on TripAdvisor, including individual scores for factors such as legroom, seat comfort, cleanliness, and more, providing a comprehensive representation of passengers' ratings and feedback on various aspects of the airline's service. Figure 7 depicts an individual passenger review, capturing their personal experience and evaluation of various parameters, including legroom, seat comfort, cleanliness, and more. The passenger's comment highlights the absence of priority boarding despite having paid for it, providing specific feedback on a particular aspect of their journey within the context of the overall evaluation presented in Figure 6.

Figure 6 | TripAdvisor overall review for easyJet

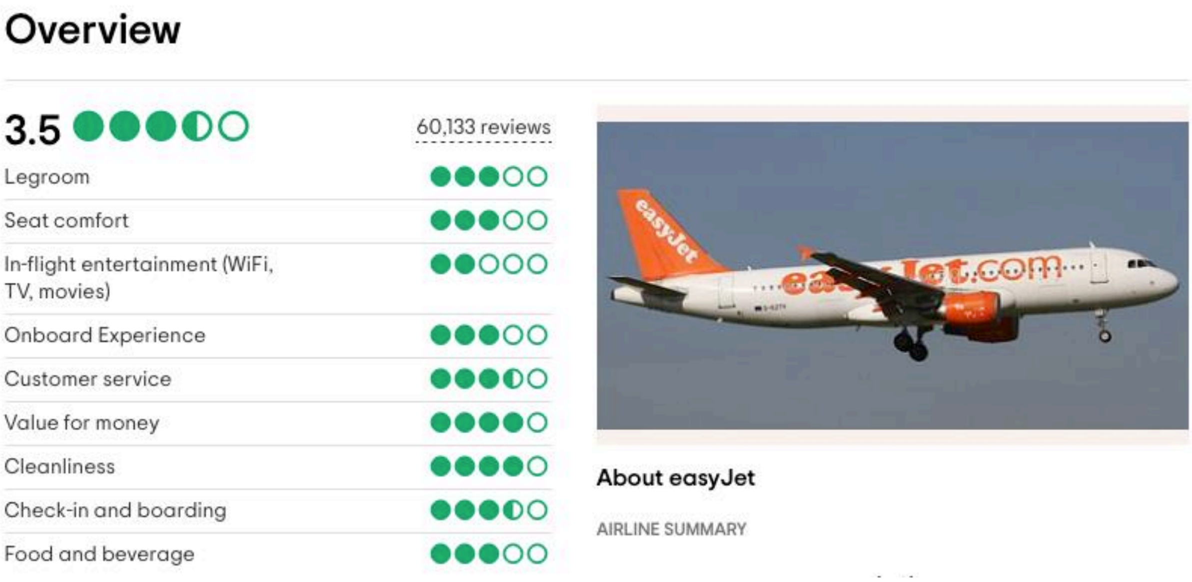
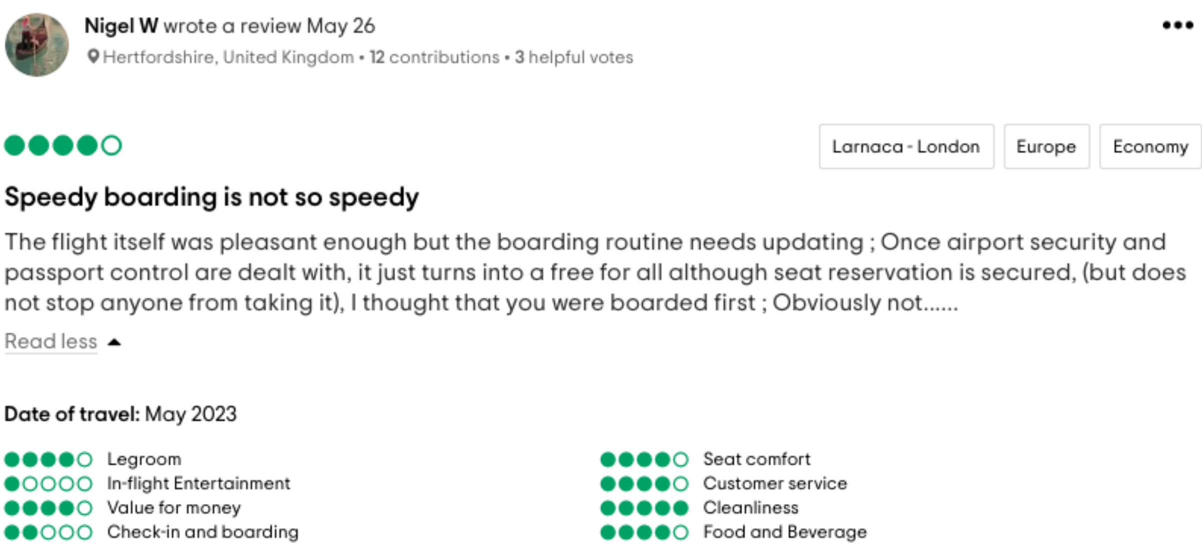


Figure 7 | Passenger's detailed review of easyJet on TripAdvisor



Reviews like the one provided in Figure 7 can be a valuable source of information for airlines, since they provide firsthand reports of the passenger experience, allowing the airlines to gain a deeper understanding about how the passenger is perceiving his/ her experience and the service received. While a score of 2 out of 5 in the check-in and boarding transmits the idea that the passenger is not particularly satisfied with those aspects, the text review provides a thorough explanation of the problem, and we can quickly understand that it is related with the priority boarding not being granted to passengers who paid for it.

However, despite the invaluable insights reviews can provide, there are also some drawbacks that airlines must consider. Firstly, each review is subjective and, therefore, represents the opinions of the passenger who wrote it. Thus, it is not always representative of the broader passenger population (Rice et al., 2017). In the case of Figure 7, there is no additional context about whether the passenger was on time in the boarding gate, consequently missing the benefit to be the first to board.

Secondly, there is no standardized evaluation criteria across different reviews (Sincero, 2012; Somekh, 2020), making it harder to analyze and compare them. As seen in the literature review, different passengers will prioritize different aspects of the travel experience, resulting in varying ratings and comments, posing a difficulty in aggregating the data for meaningful analysis.

Thirdly, since usually there are no control over who posts, and if the user actually travelled with the company or not, this could result in fake reviews (Qualtrics, 2020), distorting the reliability of the data. Additionally, there is the possibility of having an imbalance of positive/ negative reviews, since passengers may be more inclined to write a review if they had a bad experience – and even though the bad experience was not caused by a bad service in all of the airline's service, an angry passenger might lose his/ her objectivity, and attribute a negative mark to all parameters in an attempt to penalize the airline.

Finally, the huge volume of reviews can be overwhelming, making it practically impossible to manually check each review. Luckily, there are methods available, like Natural Language Processing, that encompasses sentiment analysis. By applying sentiment analysis to passenger reviews (Song et al., 2020), airlines can not only identify in an automated way which dimensions of service are most referenced, but can also classify each review as positive, negative, or neutral, providing an overall sentiment score. This helps to measure the general satisfaction level of passengers and identify specific areas of improvement, allowing to reduce the problems described in the first paragraph – one thing is one passenger complaining about not being given priority boarding even though he/ she paid for it – the other thing is multiple passengers complaining about the same thing. And this can be achieved without having human resources reading all the reviews available to retrieve this valuable information.

Airlines can also assess passenger satisfaction levels recurring to operational performance metrics, such as the punctuality of flights, flight disruptions, problems in the baggage handling, among others. Nevertheless, one of the most important ways is through surveys and feedback forms, where airlines can collect direct feedback from their passengers.

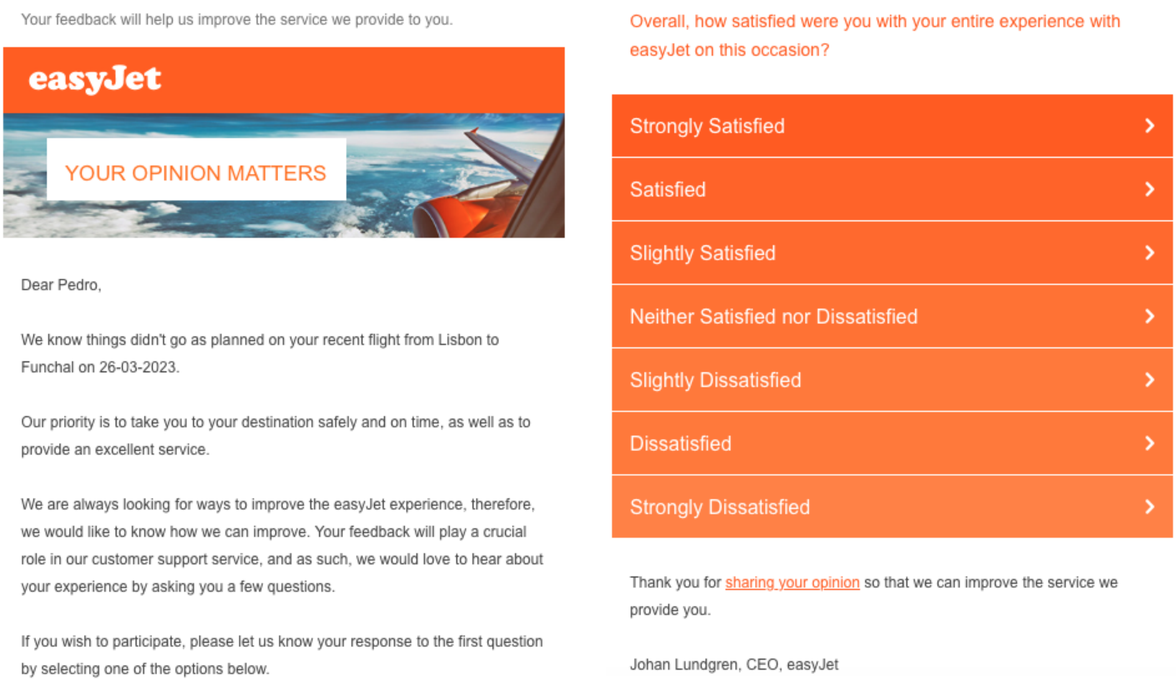
When compared to review websites and social media, surveys have the advantage of providing airlines with greater flexibility and in-depth insights. Firstly, surveys offer the flexibility to ask specific questions and offer response options that are aligned with what the airline wants to know (Somekh, 2020). This allows for a focused collection of feedback on dimensions that are of particular interest to the airline. For example, let us consider a scenario where an airline recently implemented a new in-flight Wi-Fi service and wants to assess customer satisfaction with this new offering. They can include specific questions in the survey, such as "How satisfied are you with the quality and speed of the in-flight Wi-Fi?" or “How satisfied are you with the prices charged for in-flight Wi-Fi?”, or even "To what extent did the availability of in-flight Wi-Fi improved your overall travel experience?".

By collecting feedback through surveys, the airline can gather specific insights on passengers' perception of the new Wi-Fi service, allowing them to evaluate its effectiveness. This approach enables the airlines to monitor customer satisfaction with the specific aspects they have modified, gaining valuable insights to inform their decision-making process and improve their services accordingly. If any airline was dependent on online reviews alone, there would be a risk of insufficient available feedback to understand the positive or negative reception of the new offering.

Secondly, surveys allow airlines to have control over which passengers they want to get feedback from – and to ensure that passengers responding have actually travelled with them. They can target specific demographics, customer segments, specific routes, ensuring a representative and diverse sample for more accurate analysis and decision-making. Thirdly, surveys generally yield a more balanced representation of satisfied and unsatisfied passengers, whereas online reviews tend to have a higher tendency to be overrepresented by unsatisfied passengers.

Lastly, airlines also have the possibility of combining different methods. Figure 8 shows the implementation of an integrated approach by easyJet, combining operational metrics – in the case of the figure, a flight that was delayed – with direct passenger feedback through a satisfaction survey.

Figure 8 | easyJet Passenger Satisfaction Survey Email



The flight in question was delayed, so easyJet sent an email to the passenger acknowledging that not everything went well and reinforcing their intentions to provide an excellent service – showing to the passengers that they care. After that, they ask the passenger to collaborate on a survey, which starts by asking what the overall satisfaction with the airline in this occasion was. Once the first question is answered, the passenger is directed to an online survey that covers various aspects of the journey, starting from the check-in process, continuing through all the flight experience, and concluding upon arrival when collecting the luggage at the destination.

There are various options for airlines to analyze the data coming from surveys. They can use techniques such as confirmatory factor analysis or structural equation modelling (Medina-Muñoz et al., 2018; Suki, 2014), to understand the underlying factor structure of passenger satisfaction, or through machine learning (Hulliyah, 2021; Jain et al., 2019; Jiang et al., 2022), enabling predictive capabilities. In the case of surveys like the one in Figure 8, since there is an indicator of overall satisfaction with the experience, and a group of different features like seat comfort, cleanliness of the aircraft, among many others, it is possible for airlines to use a set of algorithms known as classification algorithms, which are discussed in the next section.

3.2. Machine Learning: Classification Algorithms

To put it simply, Machine Learning (ML) is the science of programming computers, so that they can learn from data, allowing them to improve performance on specific tasks through experience and data analysis. Two of the major categories of ML are supervised and unsupervised algorithms (Géron, 2019).

Supervised learning relies on labeled data to guide the ML model and make predictions based on provided target outputs. In contrast, unsupervised learning explores unlabeled data to discover patterns and relationships without predefined target variables (Géron, 2019). For instance, in supervised learning, a model can classify emails as spam or non-spam using labeled examples, while in unsupervised learning, clustering algorithms can group similar documents based on their content without any predefined categories.

Most of the times, classification problems are tackled by using supervised learning. These algorithms try to learn the relationship that exists between a set of feature variables (attributes), and a target variable of interest (the class to which every observation belongs to). So, when presented with a new set of feature variables, the classification algorithms aim to predict or assign the appropriate target variable or class label based on the learned patterns and relationships from the training data[13].

[13] The concept of training data is explained in the next section.

In the context of air passenger satisfaction, it may come as something like:

$$f\text{(flight punctuality, seat comfort, entertainment, food and drinks, booking convenience)} \\ \rightarrow \text{passenger satisfaction}$$

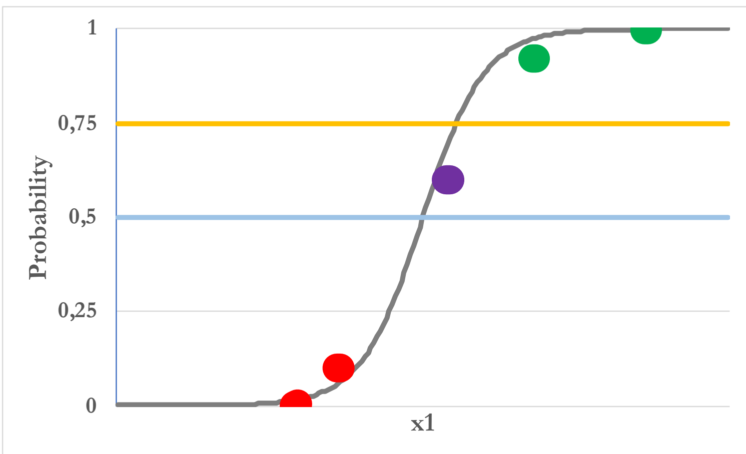
where the passenger satisfaction can have, for example, two labels: satisfied or dissatisfied. There are algorithms that can predict more than two labels, but in this dissertation the focus is on problems that require classifying data into one of two classes – also called binary classifiers.

The problem of classification can be expressed as "given a set of training data points along with associated training labels (classes), determine the class label for an unlabeled test instance" (Aggarawal, 2015, p. 2). In this section, some of the main classification algorithms are presented.

3.2.1. Logistic Regression

Logistic regression is a binary classification model that predicts the probability of an instance belonging to a specific class. It applies a logistic function to the linear combination of input features, mapping the output to a value between 0 and 1 (Géron, 2019). Figure 9 shows an example of a univariate logistic regression, which is predicting the probability of belonging to a class based on only one feature. In the case of the Figure 9, feature x_1.

Figure 9 | Example of a univariate Logistic Regression

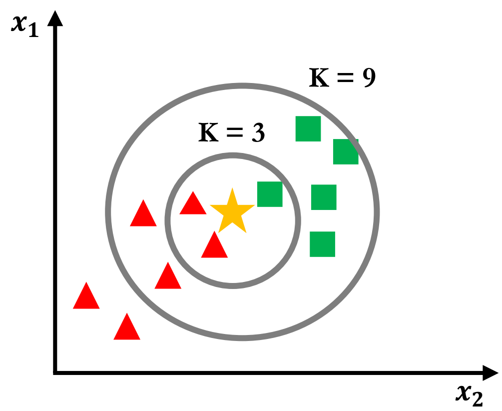


By default, the threshold is set to 50% (blue line) - data points below it (red points) are classified as not belonging to a class – in case of passenger satisfaction, dissatisfied, for example – and points above it (green and purple points) are classified as belonging to the class – passenger satisfied. However, if the threshold was set to 75% (orange line), the purple point would be classified as a dissatisfied passenger, and not as a satisfied passenger. The choice of this threshold value can have an important impact on the quality metrics of a given classifier.

3.2.2. K-Nearest Neighbors

K-Nearest Neighbors (KNN) is an algorithm that finds the K closest data points to a test instance and predicts its label or value based on the neighbors majority or average value (Aggarawal, 2015). Figure 10 shows an example of the KNN algorithm, classifying a data point represented by a yellow star, based of two features, x_1 and x_2.

Figure 10 | Example of K-Nearest Neighbors

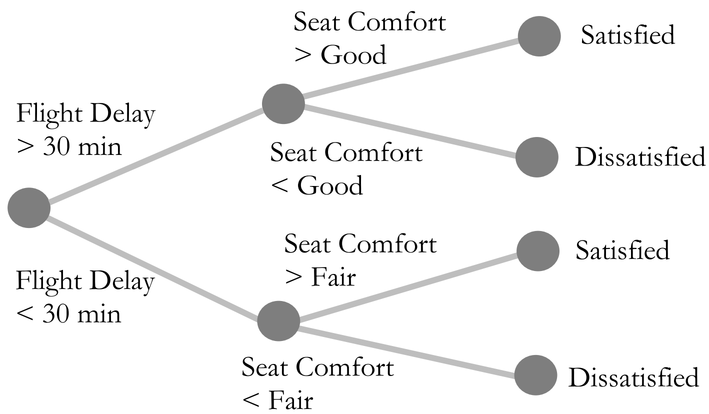


The choice of K, the number of neighbors, is a crucial parameter that affects the algorithm's performance. For instance, when classifying the star point with a **K = 3**, since the 3 closest neighbors are two triangles and one square, the star would be classified as belonging to the triangle class. However, when using **K = 9**, the 9 closest neighbors are 4 triangles and 5 squares. Thus, in this case, the star would be classified as belonging to the square class instead. However, regardless of the value of **K** chosen, the real class of the star remained the same. Another thing that significantly impacts the result of this algorithm is the calculation of the distance between two points: considering the set of attributes, there are usually several different distance metrics that can be used.

3.2.3. Decision Trees and Random Forests

Decision Trees have, as the name says, a structure similar to trees, where each node represents a feature, each branch represents a decision rule based on that feature, and each leaf corresponds to a predicted outcome (Géron, 2019). Figure 11 shows an example of a decision tree based on two features: flight delay and seat comfort.

Figure 11 | Example of a Decision Tree



Based on Figure 11, it is easy to derive some rules: if a flight is delayed more than 30 minutes, a passenger will only be satisfied if the seat comfort is better than good. Otherwise, if there is no significant delay, the passenger will be satisfied with a seat that is better than fair. Real decision trees have more nodes and branches, consider larger number of attributes, creating more complex rules in the sense that a given classification can be reached by different combinations of thresholds applied to the different attributes.

The attributes that appear in each one of the tree levels, as well as the definition of the rules are automatically set by the classification algorithm. One of the main advantages of this method is the fact that the final classification model is truly interpretable: it is easy for a human decision-maker to understand how the classification decisions are being reached.

Random Forests combine multiple decision trees to make a prediction. It works by creating a collection of decision trees, each trained on a different subset of the data. The final prediction is then determined by aggregating the predictions of all the individual trees, through majority voting (Aggarawal, 2015), or other aggregation rule. It is also possible to present just a subset of all the available attributes, usually randomly chosen, to different trees in the forest.

3.2.4. Other Classification Algorithms

In this section, four additional classification algorithms are introduced: the Naïve Bayes classifier, Support Vector Machines, Neural Networks and Multivariate Adaptive Regression Splines. These algorithms are presented in a separate section to provide a concise overview of their key concepts and functioning. While detailed explanations of each algorithm are not provided here, they are equally largely used in ML and offer different, but useful, approaches to solving classification problems.

The **Naive Bayes classifier** is an algorithm based on the Bayes' theorem. It assumes that all features are independent of each other, hence the "naive" assumption. This algorithm calculates the probability that a data point belongs to a particular class based on its features probabilities. It is widely used in text classification, spam filtering, and sentiment analysis due to its efficiency and effectiveness, especially when dealing with big datasets (Aggarawal, 2015).

Support Vector Machines (SVM) work by finding the optimal hyperplane that separates different classes in the feature space. SVM aims to maximize the margin between the classes, which leads to better generalization and improved performance on unseen data (Aggarawal, 2015).

Neural Networks (NNet) are powerful for classification tasks. They consist of interconnected layers of artificial neurons that can learn and recognize complex patterns in data, allowing them to make accurate predictions and classify inputs into different classes. By adjusting the weights and biases of the neurons during training, neural networks can effectively learn from data and generalize their knowledge to classify new and unseen instances (Aggarawal, 2015; Géron, 2019).

Multivariate Adaptive Regression Splines (MARS) is a regression method that uses a set of simple straight lines to make predictions. It is great for tough problems where there are lots of input variables and complicated non-linear connections. By putting together these straight lines, called splines, MARS builds a model that can handle the complexities of the data. It does this by tweaking and combining the splines in a step-by-step process until it finds the best fit. The result is a model that can capture the tricky relationships between the inputs and the target variable, making MARS a useful tool for regression and classification tasks (Brownlee, 2020b; Kuhn & Johnson, 2013).

There is also the alternative of considering ensembles: instead of choosing one single classification algorithm, several can be used at the same time and then the corresponding results merged using a given rule (like the majority rule). Each classifier can be seen as a different expert giving its opinion. The overall result will take into consideration the opinion of all of them. Ensembles are based on the assumption that different classifiers will tend to make mistakes differently, and by different reasons, being unlikely that all of them will make mistakes following the same trend. So, diversification can lead to increased accuracy.

3.3. Good Practices in Machine Learning

ML based projects can have an important impact for decision making problems, since ML can give important insights taking into account available data. However, for the obtained results to be valuable and to make sure they are not biased, a set of good practices must be followed. In this section, some of these good practices to consider when undertaking an ML project are presented.

3.3.1. Pre-Processing

In ML problems, raw data typically can never be used directly. This is due to many reasons, such as some ML algorithms requiring data to be numbers and statistical noise and errors needing to be corrected. There can also be the case that outliers exist and should not be considered (when anomaly detection is not the objective, since in that case outlier identification is sometimes the main focus). Datasets can also have missing values that must be dealt with. Thus, data should be pre-processed before being used by an ML algorithm. Some common tasks include data cleaning, feature selection, data transformation, feature engineering, and dimensionality reduction. These tasks involve identifying and correcting data errors, selecting relevant variables, adjusting variable scales or distributions, creating new variables, and reducing data dimensionality. These practices contribute to improving model performance and generating valuable insights from the data (Brownlee, 2020a).

For example, when dealing with a dataset that includes passenger ages, outliers or unrealistic values (such as a passenger with an age of 150 or -10 years) can be identified and addressed. Additionally, missing values are a common challenge that requires handling, either through statistical techniques for imputation or by removing the corresponding records or attributes. Another consideration is that ML algorithms typically operate on numeric data, making it necessary to transform categorical data into a numeric representation, although nowadays many of the ML existing implementations can handle categorical variables in a very straightforward way, with no need for user intervention. And even with all numeric features, sometimes it is important to normalize them, especially when the values associated with these attributes have relatively different numerical scales.

When a given attribute is skewed, other data transformations can also be performed, like applying logarithmic functions, since some models give better results when looking at close to normal distributed data. By addressing these issues, the dataset is prepared for further analysis and modeling. One very important practice that should not be forgotten is to clearly document and state all the data transformation steps that were performed, from the raw data to the data that is the input to the ML models and algorithms.

In any predictive modeling project, it is common to encounter the need for data preparation, even if the raw data consists solely of numerical values. With numerous ML algorithms available, it becomes challenging to determine the most suitable one for the task at hand, especially because each algorithm comes with its own set of requirements and expectations concerning the data: some algorithms perform worse if there are features that are irrelevant to the target, others if there are two features that are highly correlated (in which case one of them may need to be removed), and others, while disregarding these specificities, require a large quantity of data (Brownlee, 2020a).

The choice of algorithms and the data itself are interconnected, creating a dynamic relationship. Algorithms impose specific expectations on the data, each needing appropriate preparation to meet these requirements. On the other hand, the nature of the data can offer valuable insights into the algorithms that are more likely to yield effective results. Therefore, understanding this interconnection between the data and algorithm selection is crucial in achieving successful outcomes in ML projects (Brownlee, 2020a).

3.3.2. Train, Test and Validation Data

When considering supervised learning, a test dataset and a training dataset are two distinct subsets of the original dataset that must exist. The training dataset is used to train the ML model. It consists of a set of labelled examples, where both the input data and the corresponding target or output values are known. The model learns from these examples by adjusting its internal parameters, minimizing the prediction error (Brownlee, 2017). As the model was trained with this dataset, assessing its behavior with the same dataset would not be a correct measure of its performance: it would, for sure, yield much better results that would not be achieved when in the presence of unseen data.

The test dataset, on the other hand, is used to evaluate the performance of the model that was trained earlier. It should only contain data that the model has never seen before during the training phase. The model makes predictions on this dataset, and the predicted outputs are compared to the actual known outputs. This evaluation helps to understand how well the model generalizes to new and unseen data, providing an estimate of its performance in real-world scenarios (Brownlee, 2017). Actually, a model can behave extremely well in the training dataset and the results can be quite poor in the test set: if this is the case we are, probably, in the presence of overfitting which implies a lack of generalization capability of the model.

There are multiple ways to separate datasets, each with its own advantages and disadvantages. One common method is random splitting, where the dataset is randomly divided into a training set and a testing set. This approach is simple to implement and provides a quick way to evaluate the model performance. However, a potential disadvantage of random splitting is that it does not guarantee an even distribution of classes or target variables in the training and testing sets. As a result, there is a possibility of imbalanced representation, which can impact the model ability to generalize to unseen data (Kuhn & Johnson, 2019).

Another method is stratified splitting, which ensures that the distribution of classes or target variables is maintained in both the training and testing sets. This can be particularly useful when dealing with imbalanced datasets where certain classes are underrepresented. By preserving the class distribution, stratified splitting allows the model to learn from a representative sample of each class. However, a limitation of stratified splitting is that it may introduce a degree of bias if the class distribution in the dataset does not accurately reflect the real-world distribution. It assumes that the class proportions in the dataset are representative of the population, which may not always be the case (Kuhn & Johnson, 2019).

K-Fold Cross-validation is another widely used method for dataset separation. It involves dividing the dataset into K subsets or "folds" and performing model training and evaluation iteratively. In each iteration, one fold is used as the testing set, while the remaining folds are combined to form the training set. This allows for a comprehensive evaluation of the model performance across different subsets of the data. Cross-validation is particularly advantageous when the dataset size is limited, as it maximizes the utilization of available data. However, one potential disadvantage of cross-validation is increased computational complexity, as it requires running the model training and evaluation multiple times (Alhamid, 2020).

All in all, the use of separate test and training datasets helps prevent overfitting (Kumar, 2020) and it allows for a more objective understanding of the model performance and its ability to make accurate predictions on unseen examples (Brownlee, 2020a).

When there are several ML models that can be used, and the objective is also to select one out of a set of possible ML alternatives, then it is sometimes advisable to use a validation set: this subset of the initial dataset, that has no intersection with either the training or testing datasets, can be used to assess the quality of the chosen ML model.

3.3.3. Performance Metrics

Once compared the predictions made by the algorithm and the real labels, it is important to use metrics to understand how the model performed. A confusion matrix provides a summary of the predictions made by the model compared to the actual values of the target variable. Table 5 shows an example of a confusion matrix, assuming a binary classification problem with labels satisfied and dissatisfied.

Table 5 | Confusion Matrix

		Predicted	
		Satisfied	**Dissatisfied**
Actual	**Satisfied**	# True Positives (TP)	# False Negatives (FN)
	Dissatisfied	# False Positives (FP)	# True Negatives (TN)

Accuracy is a metric that measures the proportion of correctly classified instances among the total number of instances.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions\ Made} = \frac{TP + TN}{TP + TN + FN + FP}$$

Accuracy, even though widely used, does not always provide a complete picture, especially when dealing with unbalanced datasets (when the distribution of classes is uneven, with one or more classes having significantly fewer instances compared to others). It also gives the same importance to false negatives and positives, which in some cases may not be wise to do. Nevertheless, other measures can be considered (Mishra, 2020).

Precision is a metric that quantifies the proportion of correctly predicted positive instances out of all instances predicted as positive.

$$Precision = \frac{Number\ of\ Correct\ Positive\ Predictions}{\#\ Correct\ Positive\ Predictions + \#\ Wrong\ Positive\ Predictions} = \frac{TP}{TP + FP}$$

Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive instances that are correctly identified as positive by the model.

$$Recall = \frac{Number\ of\ Correct\ Positive\ Predictions}{\#\ Correct\ Positive\ Predictions + \#\ Wrong\ Negative\ Predictions} = \frac{TP}{TP + FN}$$

The F1 Score is an alternative way to measure the model's accuracy, and it tries to find a balance between precision and recall.

$$F1\ Score = 2 \times \frac{1}{\frac{1}{precision} + \frac{1}{recall}}$$

The F1 Score penalizes the model if there is a significant difference between precision and recall, ensuring that both aspects of performance are considered and encouraging a balance between them. Therefore, the F1 Score approaches 1 only if both precision and recall are high. For example, if the precision is 0,9 but the recall is 0,3, the F1 score is 0,54, indicating a trade-off between precision and recall and highlighting the need for a more balanced performance.

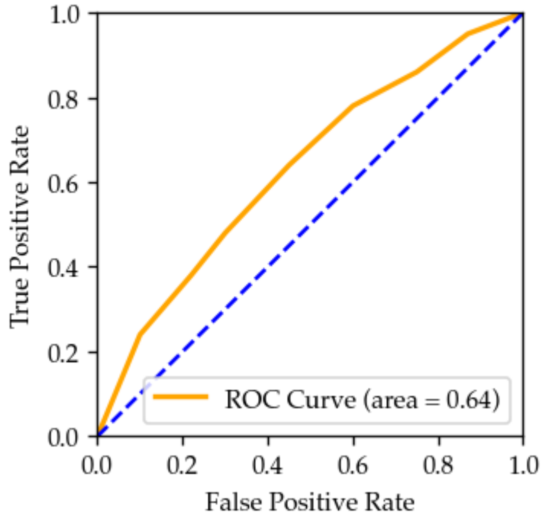
The false positive rate (FPR) corresponds to the proportion of data that is negative, but wrongly predicted as positive:

$$FPR = \frac{Number\ of\ Wrong\ Positive\ Predictions}{\#\ Negative\ Correct\ Predictions + \#\ Wrong\ Positive\ Predictions} = \frac{FP}{TN + FP}$$

When combining the True Positive Rate (also known as Recall) with the False Positive Rate, calculated for different thresholds (by defining different boundaries between two classes in a binary classification problem), we can draw the ROC (receiver operating characteristic) curve, exemplified in Figure 12. All the classification models will give as a result a value between 0 and 1. The ROC curve presents these values for the different classification results that would be obtained when different thresholds are considered to define whether each given observation belongs to the class or not. The ideal ROC curve, in Figure 13, would be such that, independently of the considered threshold, the model would be right 100% of the times.

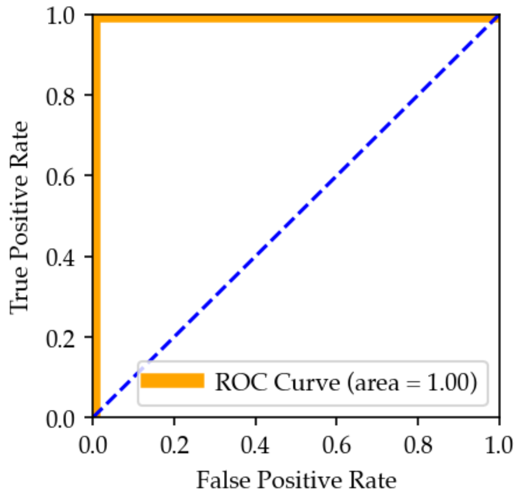
The Area Under the Curve (AUC), which is the area under the ROC curve, is also an overall performance metric used for binary classification models. The AUC value ranges from 0 to 1, where a value of 1 indicates a perfect classifier, and a value of 0,5 represents a random classifier (it means it does not perform better than a random guess, assuming a balanced dataset). The higher the AUC, the better the model ability to distinguish between positive and negative instances. AUC is commonly used as a metric to compare and evaluate different classifiers (Hosmer et al., 2013). Actually, the objective is to find classifiers that are the furthest away from the behavior of a random classifier: if a classifier has an AUC of 10%, this means that we can simply invert its result and get a classifier that has an AUC of 90%.

Figure 12 | ROC Curve and AUC



Source: Author

Figure 13 | Perfect ROC Curve



Source: Author

3.4. Empirical Study

3.4.1. Introduction

The dataset used in this study is the Airline Passenger Satisfaction obtained from Kaggle[14], being derived from a survey conducted among passengers of an USA airline. This is a free, open-source dataset, with no restrictions considering its use.

[14] https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction

Using a dataset derived from a survey has some advantages over relying, for example, on data collected from online reviews. Unlike online reviews, the survey data provides an additional layer of security, ensuring that the respondents are indeed passengers that traveled with the airline. Furthermore, the standardized format of surveys enables the collection of specific and targeted information according to the airline desired metrics, with the desired scale. This consistency in data collection and alignment with the airline predefined scale improves the reliability and comparability of the results obtained from the study.

While utilizing a dataset derived from a survey offers several advantages, it is important to acknowledge the potential limitations compared to online reviews. Survey data may not capture real-time or spontaneous feedback as effectively as online reviews, which are often posted immediately after a travel experience. Additionally, surveys typically gather data at a specific point in time, which may not capture evolving factors that can impact passenger satisfaction.

Having said this, the goals of the study are to analyze and determine some of the factors that contribute to passenger satisfaction. Additionally, this study also intends to develop a model that can predict with some degree of accuracy whether a passenger was satisfied or not with his/ her experience, especially considering that the satisfaction a passenger gets is usually not dependent on one single factor, but on the combination of multiple factors. By achieving these goals, this study aims to provide valuable insights and methods for airlines to enhance customer satisfaction and improve overall service quality.

3.4.2. Exploratory Data Analysis

The dataset used in this study comprises 129.880 responses obtained from an airline survey conducted to evaluate the satisfaction level of passengers based on various factors. For each record, there is one of two labels associated with it: Satisfied or Neutral/ Dissatisfied. The reason for two labels in one single class is that airlines might only be interested in figuring out what makes a passenger satisfied, considering a neutral passenger as bad as a dissatisfied one. The characteristics of the respondents are present in Table 6.

Table 6 | Characteristics of the survey respondents

Characteristic		Percentage	Characteristic		Percentage
Gender	Female	50,7%	**Customer Type**	Loyal	81,7%
	Male	49,3%		Disloyal	18,3%
Age	1-18	8,5%	**Type of Travel**	Personal	30,9%
	19-36	33,5%		Business	69,1%
	37-54	39,8%	**Class**	Economy	44,9%
	55-72	17,7%		Economy Plus	7,3%
	73-90	0,5%		Business	47,9%

n=129.880

The dataset exhibits gender balance, and the age distribution roughly follows a normal distribution. Similarly, there is an equitable representation of passengers in both Economy and Business Class categories. Additionally, the dataset presents a significant proportion of loyal passengers who travel for business purposes, whereas there is a comparatively lower representation of disloyal passengers traveling for personal reasons, which includes tourism and visiting family, among others.

Table 7 presents and characterizes the set of attributes that are available for each record in the dataset. Most of these features are represented by values ranging from 0 to 5. A value of 0 indicates "Non applicable" for the feature, while values from 1 to 5 correspond to a Likert scale of satisfaction. In this scale, a value of 1 represents "Very Dissatisfied" and a value of 5 represents "Very Satisfied".

However, there are three exceptions to this pattern: Flight Distance, Departure Delay in Minutes, and Arrival Delay in Minutes. These features are numerical measurements and have values starting from 0 without an upper limit, as they represent flight distance and duration of delays rather than subjective satisfaction ratings.

Appendix A shows a detailed distribution of the different features in Table 7.

Table 7 | Dataset Additional Features Characteristics

Features	Mean	Standard Deviation	# Non Applicable	Minimum	Q1	Median	Q3	Maximum
Flight Distance	1190,31	997,45	0	31	414	844	1744	4983
Inflight Wi-Fi Service	2,814	1,26	3916	0	2	3	4	5
Departure /Arrival Time Convenient	3,223	1,39	6681	0	2	3	4	5
Ease of Online Booking	2,883	1,30	5682	0	2	3	4	5
Gate Location	2,977	1,28	1	0	2	3	4	5
Food and Drink	3,208	1,33	132	0	2	3	4	5
Online Boarding	3,332	1,27	3080	0	2	3	4	5
Seat Comfort	3,441	1,32	1	0	2	4	5	5
Inflight Entertainment	3,359	1,33	18	0	2	4	4	5
On-board Service	3,383	1,29	5	0	2	4	4	5
Legroom Service	3,366	1,30	598	0	2	4	4	5
Baggage Handling	3,632	1,18	0	1	3	4	5	5
Check-in Service	3,306	1,27	1	0	3	3	4	5
Inflight Service	3,642	1,18	5	0	3	4	5	5
Cleanliness	3,286	1,31	14	0	2	3	4	5
Departure Delay in Minutes	14,71	51,82	0	0	0	0	12	1592
Arrival Delay in Minutes	15,09	52,06	0	0	0	0	13	1584

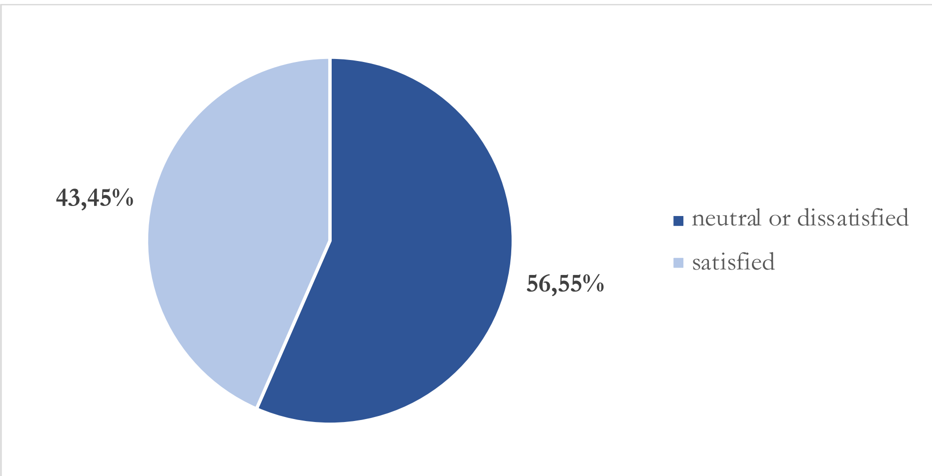
Based on Table 7, the data reveals that Inflight Service and Baggage Handling received the highest ratings among the different aspects of service. These dimensions exhibit the lowest standard deviation, suggesting a higher level of agreement among passengers regarding their positive experiences in these areas. Furthermore, approximately 6 out of 10 passengers provided a satisfaction rating of 4 or 5 for Inflight Service and Baggage Handling, indicating that the majority of passengers had positive experiences. In comparison, around 55% of passengers expressed satisfaction with Seat Comfort, demonstrating a slightly lower satisfaction rate in this aspect.

On the other hand, Inflight Wi-Fi Service and Ease of Online Booking were rated the lowest by passengers, suggesting that passengers were less satisfied with these aspects of the service. The higher standard deviation for these dimensions indicates more variability in the ratings, suggesting that opinions among passengers were more diverse. For these two dimensions, only 3 out of 10 passengers expressed satisfaction.

Furthermore, passengers experienced an average delay of approximately 15 minutes, suggesting a moderate level of delay throughout the dataset. However, it is important to note that there was a significant delay of around 26 hours, indicating a potential outlier or an exceptional case of prolonged delay. Regarding flight distances, passengers traveled an average distance of 1190. However, the relatively large standard deviation of 997 indicates a considerable dispersion in the distances flown.

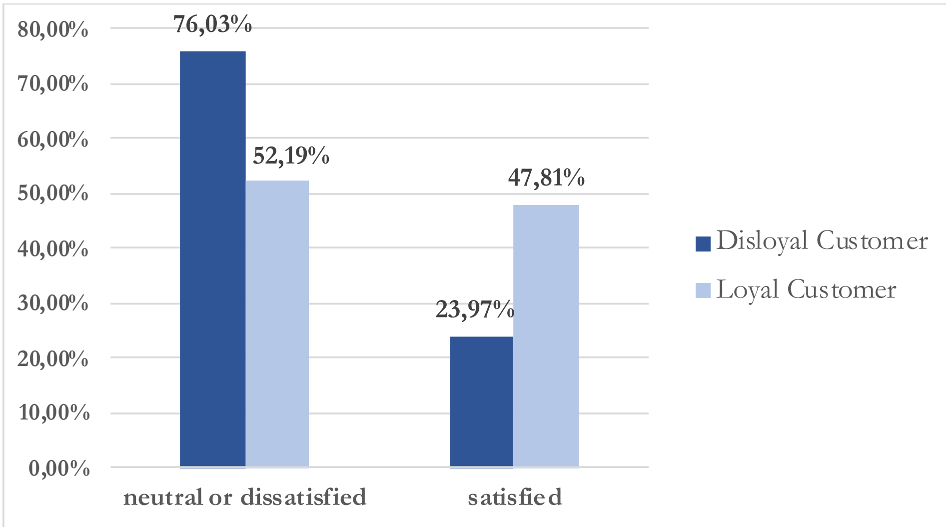
In terms of distribution between Satisfied and Neutral or Dissatisfied passengers, the dataset is relatively balanced, as seen in Figure 14.

Figure 14 | Satisfaction Labels Distribution



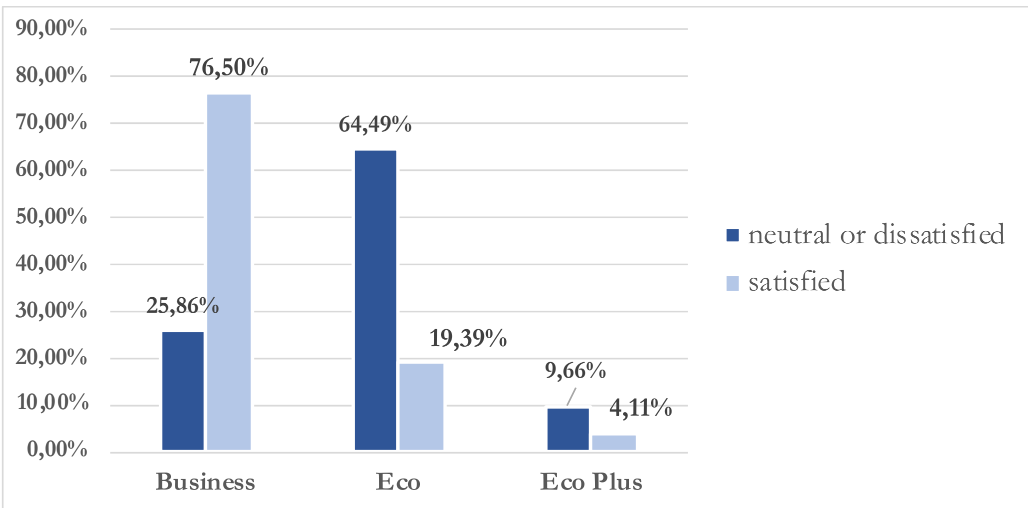
When comparing the customer type with the levels of satisfaction (Figure 15), it is evident that Disloyal Customers tend to be more dissatisfied. Even though, for Loyal Customers, there are also more dissatisfied customers, the difference is minimal when compared to Disloyal Customers. This may indicate the significance of customer loyalty in driving overall satisfaction levels.

Figure 15 | Levels of Satisfaction per Customer Type



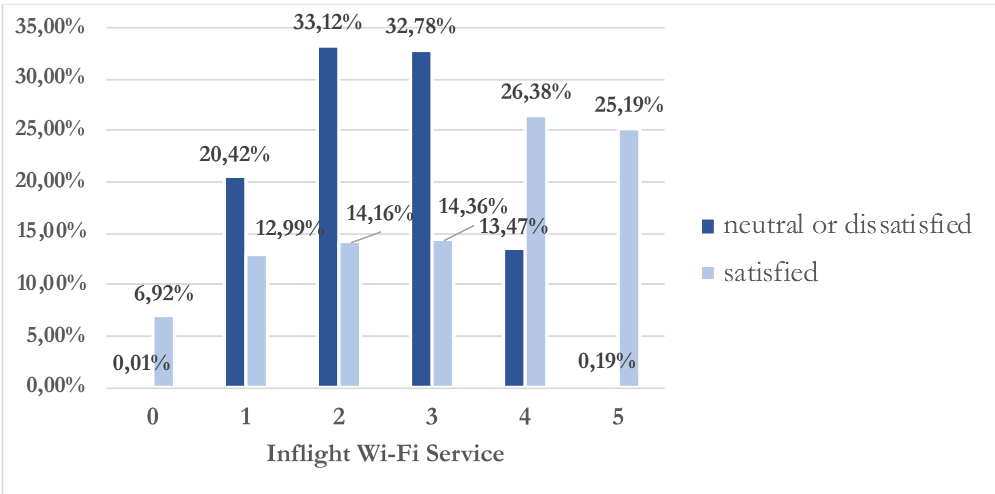
When comparing the class of travel (Figure 16), the majority of the passengers who travelled in Business Class where satisfied, whereas passengers travelling in Economy or Economy Plus were dissatisfied. This suggests that airlines should continue improving their economy product.

Figure 16 | Class of Travel and Satisfaction



Inflight Wi-Fi also seems to have an important contribution to passenger satisfaction: the great majority of the passengers who gave a rating of 5 were satisfied (Figure 17).

Figure 17 | Inflight Wi-Fi and satisfaction



Additionally, the majority of the passengers who rated the seat comfort and extra legroom with scores of 4 and 5 expressed satisfaction with their flight experience (Figures 18 and 19).

Figure 18 | Seat Comfort and Satisfaction

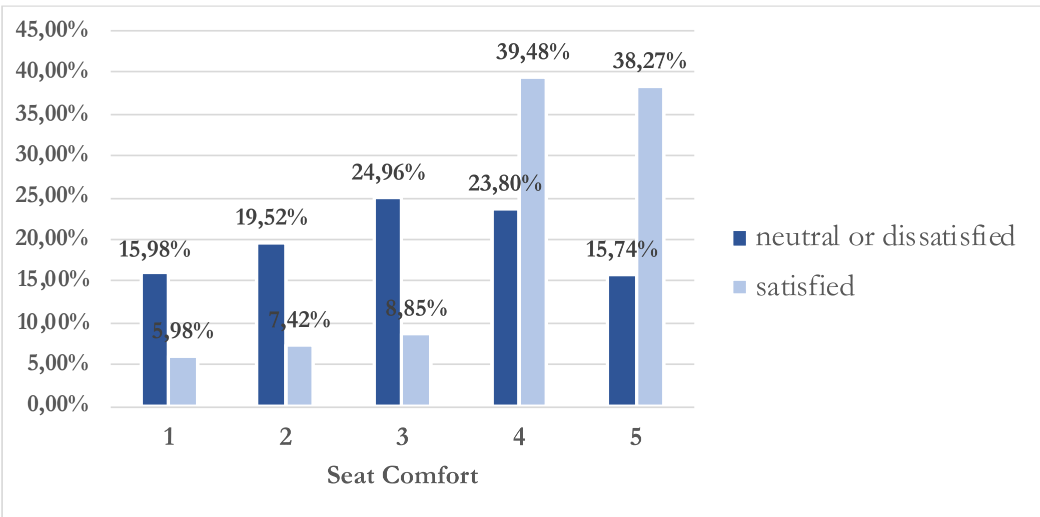
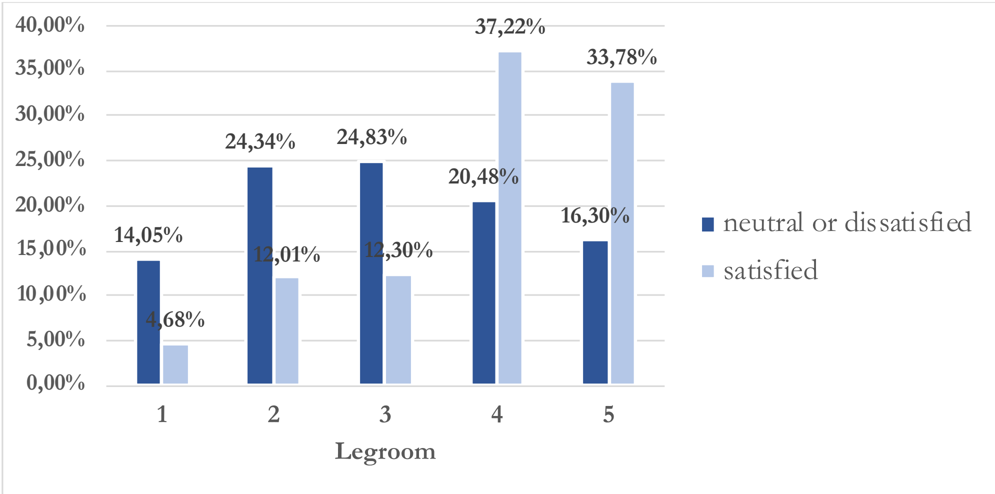


Figure 19 | Legroom and Satisfaction



In Figure 20, the influence of features such as check-in service, cleanliness, gate location, departure/arrival time convenience, in-flight entertainment, and online boarding on passenger satisfaction can be observed.

The plots show the distribution of passenger satisfaction scores for each dimension. Each plot represents scores ranging from 1 to 5, along with a category for non-applicable responses. The color displayed in each cell indicates the approximate number of rows corresponding to satisfied or neutral/dissatisfied passengers.

For instance, let us consider the Cleanliness dimension. In the plots for scores 1 and 2, it can be observed that the color is predominantly orange/brown for neutral/dissatisfied passengers and more yellow for satisfied passengers. Referring to the color bar on the right side of the Cleanliness plot, this suggests that there are considerably more records of neutral/dissatisfied passengers compared to satisfied passengers for scores 1 and 2 of cleanliness.

On the other hand, when examining scores 4 and 5, the colors associated with satisfied passengers appear darker than those associated with neutral/dissatisfied passengers. This indicates, according to the color code provided for that particular plot, that there are more satisfied passengers than non-satisfied passengers for higher cleanliness scores.

Figure 20 | Influence of Checkin service, Cleanliness, Gate Location, Departure/Arrival Time Convenience, in-flight entertainment and Online boarding on satisfaction

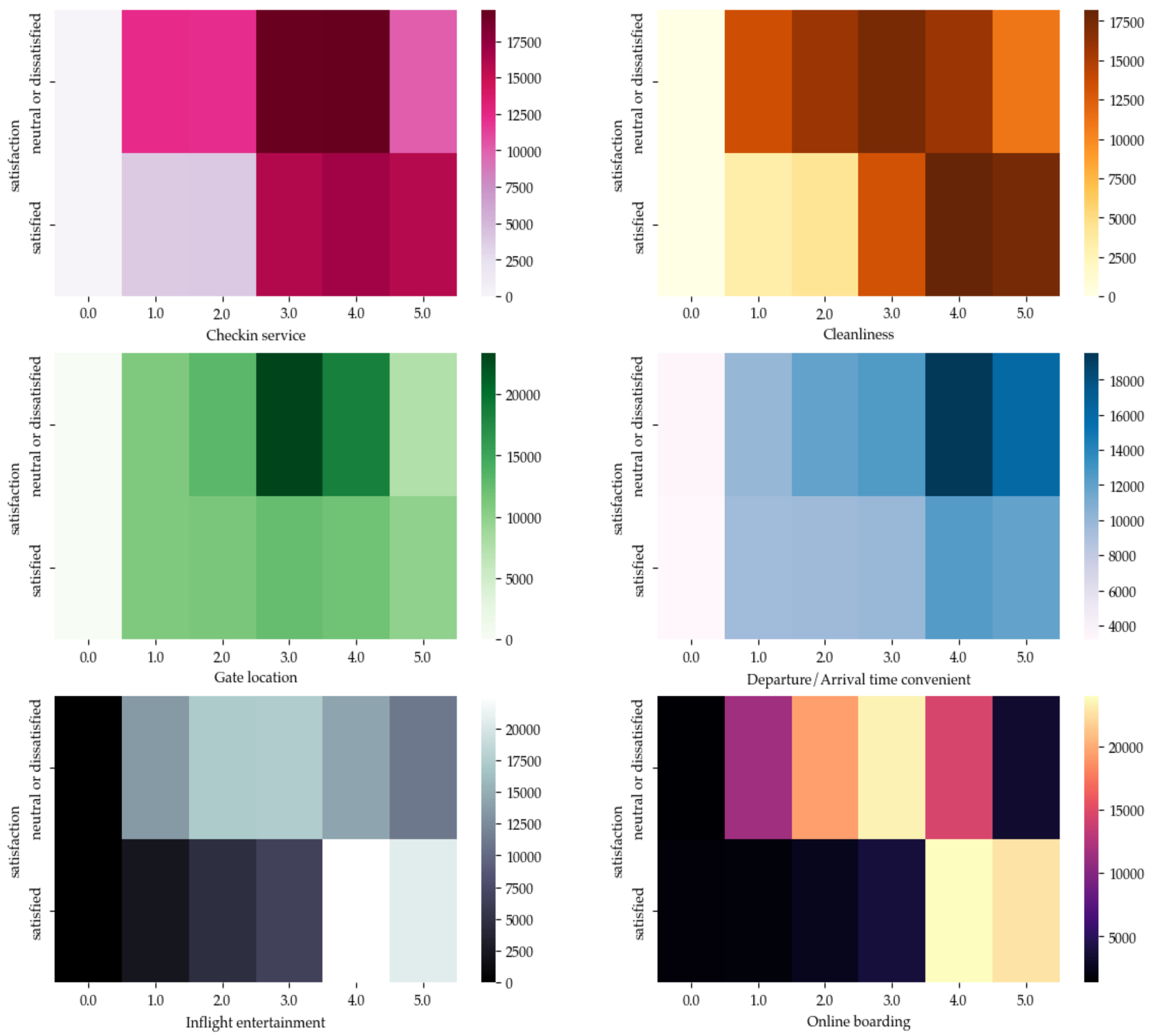


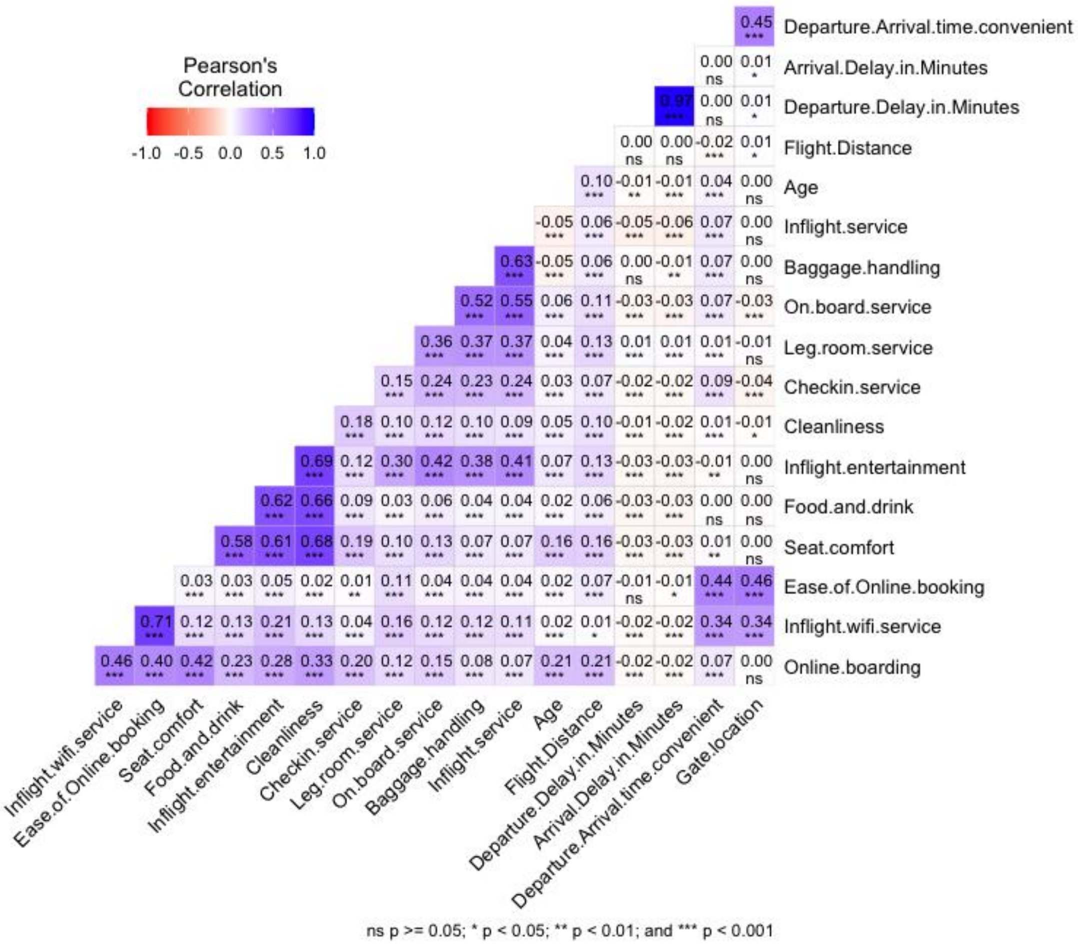
Figure 20 reveals that higher ratings for cleanliness, inflight entertainment, and online boarding are associated with greater passenger satisfaction. However, no clear relationship can be observed between check-in service, gate location, and departure/arrival time convenience and passenger satisfaction. Interestingly, there is a notable occurrence of passenger dissatisfaction despite moderate ratings of 3 or 4 for these factors, which may appear somewhat counterintuitive.

3.4.3. Data Preprocessing and Methods

In this section, the preprocessing steps data underwent to ensure its quality and suitability for analysis are described. Additionally, the application of various classification algorithms to the data will be demonstrated. For the effect, different R libraries are used (Appendix B provides an overview of the different libraries used).

The only feature with missing values is “Arrival Delay in Minutes”, with 393 missing datapoints, corresponding to approximately 0,3% of the dataset rows. Before deciding how to deal with these missing values, a correlation matrix with the numeric features was calculated using R’s library *metan*.

Figure 21 | Correlation Matrix of the numeric features



Based on Figure 21, the "Arrival Delay in Minutes" is strongly correlated with the "Departure Delay in Minutes," as evidenced by a high correlation coefficient ($r = 0.97$) and a statistically significant p-value of less than 0.001, which confirms the expected relationship, since the speed of airplanes tends to be consistent for a given route, the delay duration remains relatively constant throughout the flight, contributing to the strong correlation observed.

Given the strong correlation between "Arrival Delay in Minutes" and "Departure Delay in Minutes," removing the former feature from the analysis was deemed appropriate. Including both features would not provide additional valuable information, as they capture similar aspects of delay. Consequently, the need to handle missing values for the "Arrival Delay in Minutes" feature was eliminated.

Although several features show relatively high and statistically significant correlations, such as Ease of Online Booking and Inflight Wi-Fi Service, or Cleanliness and Inflight Entertainment, these correlations are not as strong as the relationship between Arrival and Departure Delay ($r = 0.7 < r = 0.97$), and since there is a relation of more than 7500 records per attribute, there is no need for dimensionality reduction. Therefore, all these features remain as they are.

In this study, the decision was made not to remove outliers from the dataset. Outliers are extreme values that deviate significantly from the rest of the data. While outliers can potentially affect the analysis and interpretation of the data, they can also contain valuable information or represent unique cases that are important for understanding the underlying patterns and trends (for example, the case of a passenger who suffered a delay of 26 hours). Additionally, the dataset used for this study is relatively large, which provides robustness against the influence of eventual outliers.

3.4.3.1. Random Classifier

A random classifier is used as a baseline model when evaluating the performance of the other classification models, serving as a benchmark against them. By assigning labels randomly based on a fixed probability distribution, a random classifier does not learn any patterns or relationships in the data. Therefore, its predictions are purely based on chance.

Using a random classifier allows to assess whether the other models are actually learning meaningful patterns and providing valuable predictions. If the other models cannot outperform the random classifier, this suggests that those models are not learning anything useful from the data or are performing no better than a random chance. On the other hand, if the models consistently outperform the random classifier, it indicates that the models are learning valuable patterns and are capable of making better predictions.

To create the random classifier, the following steps were taken:

1. A random real number between 0 and 1 was generated from a uniform distribution.
2. Since the neutral or dissatisfied class accounts for 56,55% of the dataset rows, the threshold of the classifier was set at 0,5655. This means that if the random number generated was below this threshold that record would be classified as neutral/dissatisfied and satisfied otherwise.
3. The R's libraries *pROC* and *caret* were used to calculate the different performance metrics of the random classifier.

The dataset used in this study can be interpreted as consisting of two distinct groups of information. The first group is composed by data that the airline can quickly and objectively obtain without relying on passenger survey responses. This includes variables such as flight duration, gender, age, delay, customer type, and so on. These factors are generally measurable and do not involve subjective judgments.

On the other hand, the second group of information encompasses subjective evaluations provided by passengers. For instance, passengers are asked to rate seat comfort on a scale of 1 to 5. While the physical attributes of the seats may remain the same, individual passengers may assign different scores based on their personal preferences, experiences or expectations. Consequently, these subjective evaluations can lead to varying levels of satisfaction amongst passengers.

If an airline is trying to predict whether a passenger was satisfied or not with his/her flight, so that it can act upon it without having to check with the passenger, the airline can only count with information similar to the one in the first group. Otherwise, when an airline checks with a passenger to obtain the information from the second group, it is not hard to get a response about the overall satisfaction of the passenger (Figure 8), therefore the need for predictive models diminishes. Nevertheless, these models can still be useful to identify the most important dimensions of what affects the passengers perception of the quality of service for the majority of the passengers.

With this in mind, in the next two sections two groups of models are built: models without personal responses from the passengers – corresponding to models that airlines can use to predict passenger satisfaction without resorting to any other source of information – and models with personal responses – allowing airlines to understand the dimensions of service passengers most value. Additionally, the objective is to assess the extent to which incorporating passengers subjective perspectives can enhance the performance of the models. This can give an idea of the importance that subjective and individual perspectives of passengers have on their overall satisfaction.

For dataset splitting into training and test datasets, R library *rsample* was used for stratified sampling, with 75% of the data used for training, and 25% for testing. This method is particularly beneficial for large datasets, like the one in this study, as it provides representative subsets without the computational expense of other methods such as cross-validation.

Additionally, the models were trained using the default parameters without hyperparameter tuning. This approach allows for a straightforward implementation without the need for extensive parameter optimization, at the expense, however, of potential reduced performance of the models.

3.4.3.2. Models without Personal Responses

In this dataset, the available variables for the models are limited, which may impact the performance. However, there are other additional variables that can be considered to enhance the analysis. These variables include the ticket price, aircraft type (such as Boeing vs Airbus and single-aisle vs double-aisle), specific departure and arrival airports (considering the distance to the city center), flight occupancy, among others. For the models in this section, the features in Table 8 from the dataset are used.

Table 8 | Features used in the models without personal responses.

Features	
Gender	Class
Customer Type	Flight Distance
Age	Departure Delay in Minutes
Type of Travel	

The ML algorithms used are present in Table 9.

Table 9 | Classification Algorithms Used and respective R Libraries

Algorithm	R Library
Decision Trees (DT)	rpart
Random Forest (RF)	randomForest
Logistic Regression (LR)	stats
Neural Networks (NNet)	caret
Multivariate Adaptive Regression Splines (MARS)	earth

Additionally, an ensemble of the five algorithms in Table 9 was employed. To combine the different predictions of each model, it was adopted the simple averaging with the next steps:

1. For each model, the probability of a passenger being satisfied was calculated.
2. The five probabilities of the five different models were averaged, with a simple average.
3. If the resulting probability was above 0.5, the passenger was considered "Satisfied". Otherwise, it would be considered "Neutral or Dissatisfied".

3.4.3.3. Models with Personal Responses

In these models, in addition to the features present in Table 8, the features in Table 10 were added.

Table 10 | Additional Features for the models with Personal Responses

<table>
<tr><th colspan="3">Features</th></tr>
<tr><td>Inflight WIFI Service</td><td>Ease of Online Booking</td><td>Food and Drink</td></tr>
<tr><td>Online Boarding</td><td>Seat Comfort</td><td>Inflight Entertainment</td></tr>
<tr><td>Legroom Service</td><td>Baggage Handling</td><td rowspan="2">Departure / Arrival time convenient</td></tr>
<tr><td>Inflight Service</td><td>Cleanliness</td></tr>
<tr><td>Check-in Service</td><td colspan="2"></td></tr>
</table>

To allow valid comparisons between the two models, in these models the same ML approaches were applied (Table 9 and Ensemble).

3.4.3.4. Feature Importance

In order to gain a comprehensive understanding of the significance of different features in relation to passenger satisfaction, the algorithm with the best overall metrics was chosen for both models. To calculate the importance of the various features, the Feature Permutation Importance method of the *iml* library was used.

The Feature Permutation Importance assesses the importance of a feature by calculating the change in the model prediction error when the feature values are permuted. If permuting the feature values leads to an increase in the model error, the feature is considered "important" because the model relied on it for accurate predictions. Conversely, if permuting the feature values does not affect the model error, the feature is deemed "unimportant" because the model ignored it when making predictions (Molnar, 2022).

This approach allowed for a detailed assessment of the contribution of each feature, improving the understanding of their impact on passenger satisfaction.

3.4.4. Results

In this section, the results of the various models tested are presented. The next section will focus on the discussion and comparison of these results.

3.4.4.1. Random Classifier

The random classifier had the performance metrics in Table 11.

Table 11 | Performance Metrics of the Random Classifier

Metric	Value	Metric	Value
Accuracy	50,83%	**Precision**	43,40%
Sensitivity	43,35%	**F1-Score**	0,4337
Specificity	56,57%	**AUC**	0,4996

3.4.4.2. Models without Personal Responses

For the different algorithms used, the performance metrics for the train dataset are summed up in Table 12 and for the test dataset are summed up in Table 13. The ensemble results, both for train and test datasets, are in Table 14.

Table 12 | Performance Metrics on the train dataset of the Models without Personal Responses

Metric	DT	RF	LR	NNet	MARS
Accuracy	79,14%	80,76%	78,38%	79,84%	78,79%
Sensitivity	72,14%	80,14%	77,08%	79,77%	77,88%
Specificity	84,51%	81,23%	79,38%	79,90%	79,49%
Precision	78,16%	76,63%	74,17%	75,30%	74,47%
F1-Score	0,7503	0,7835	0,7560	0,7747	0,7613
AUC	0,7918	0,8859	0,8406	0,8590	0,8479

Table 13 | Performance Metrics on the test dataset of the Models without Personal Responses

Metric	DT	RF	LR	NNet	MARS
Accuracy	79,24%	80,28%	78,16%	79,77%	78,41%
Sensitivity	72,07%	79,16%	77,28%	79,59%	77,34%
Specificity	84,74%	81,15%	78,84%	79,86%	79,22%
Precision	78,39%	76,33%	73,72%	75,21%	74,09%
F1-Score	0,7500	0,7772	0,7546	0,7734	0,7568
AUC	0,7935	0,8506	0,8368	0,8566	0,8458

The plotted Decision Tree (DT) is in Appendix C, Figure C – 1. For the NNet, *caret* performed hyperparameter tunning, having chosen a size of 5 and a decay of 0,1.

Table 14 | Performance Metrics on the train and test dataset of the Ensemble method of the Model without Personal Responses

Dataset	Accuracy	Sensitivity	Specificity	Precision	F1-Score	AUC
Train	79,97%	76,41%	82,70%	77,23%	0,7683	0,8700
Test	79,80%	76,09%	82,64%	77,11%	0,7659	0,8574

3.4.4.3. Models with Personal Responses

For the different algorithms used, the performance metrics for the train dataset are summed up in Table 15 and for the test dataset are summed up in Table 16. The ensemble results, both for train and test datasets, are in Table 17.

Table 15 | Performance Metrics on the train dataset of the Models with Personal Responses

Metric	DT	RF	LR	NNet	MARS
Accuracy	89,83%	100%	93,52%	95,46%	93,27%
Sensitivity	90,34%	100%	91,52%	92,76%	91,17%
Specificity	89,45%	100%	95,05%	97,53%	94,89%
Precision	86,80%	100%	93,42%	96,65%	93,20%
F1-Score	0,8853	1	0,9246	0,9467	0,9217
AUC	0,9279	1	0,9798	0,9913	0,9779

Table 16 | Performance Metrics on the test dataset of the Models with Personal Responses

Metric	DT	RF	LR	NNet	MARS
Accuracy	89,86%	96,41%	93,02%	95,66%	91,92%
Sensitivity	90,35%	94,60%	91,15%	93,15%	89,49%
Specificity	89,49%	97,81%	94,45%	97,59%	93,78%
Precision	86,85%	97,06%	92,65%	96,75%	91,70%
F1-Score	0,8856	0,9582	0,9189	0,9491	0,9058
AUC	0,9274	0,9946	0,9777	0,9917	0,9693

The plotted Decision Tree (DT) is in Appendix C, Figure C – 2. For the NNet, *caret* performed hyperparameter tunning, having chosen a size of 5 and a decay of 0,1.

Table 17 | Performance Metrics on the train and test dataset of the Ensemble method of the Model with Personal Responses

Dataset	Accuracy	Sensitivity	Specificity	Precision	F1-Score	AUC
Train	94,91%	93,01%	96,37%	95,17%	0,9408	0,9928
Test	93,86%	91,90%	95,37%	93,84%	0,9286	0,9860

3.4.4.4. Feature Importance

Figure 22 | Feature Importance of the model without Personal Responses

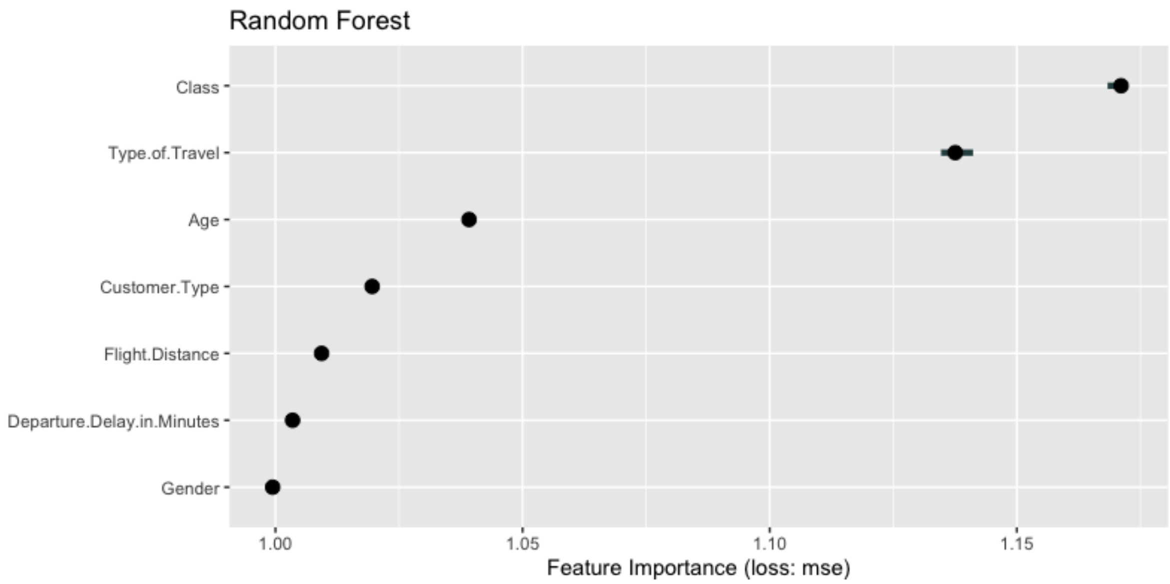
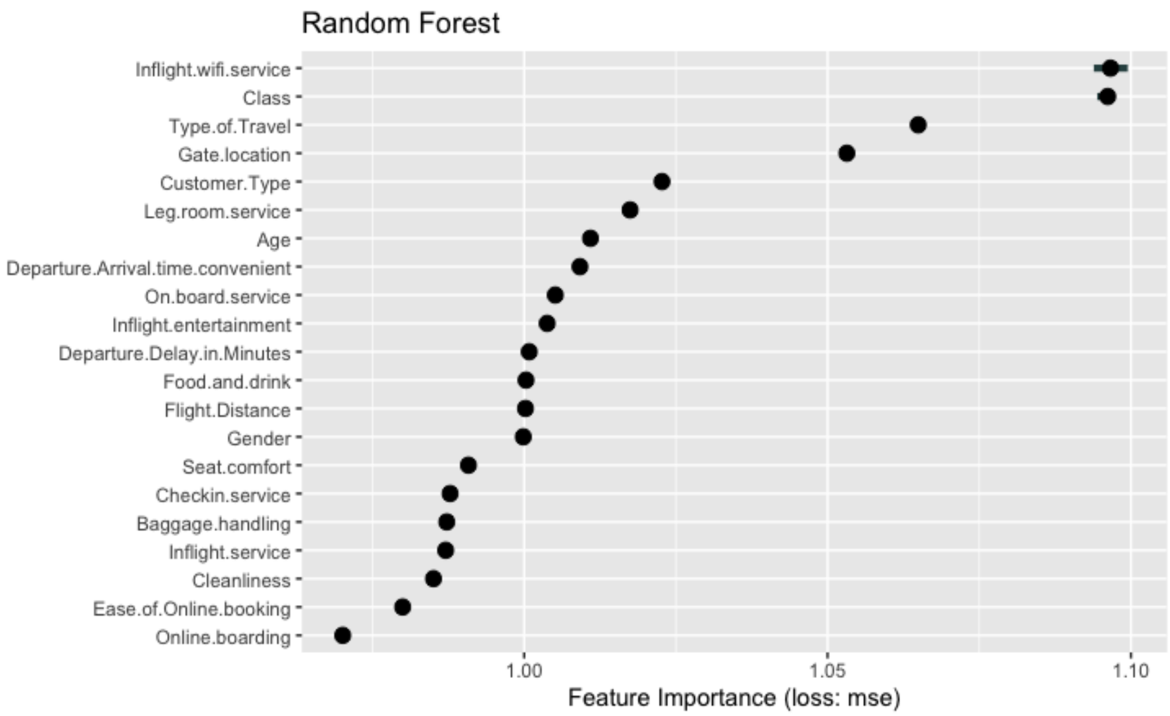


Figure 23 | Feature Importance of the model with Personal Responses



3.4.5. Discussion

The results obtained from the model without personal responses were unexpectedly promising. All five tested algorithms demonstrated superior performance compared to random guessing, achieving an average accuracy of 79% compared to the baseline accuracy of 51%. Furthermore, the F1-Scores and AUC averaged at 0.76 and 0.84, respectively, outperforming the random classifier's scores of 0.43 and 0.50, respectively.

These impressive metrics are particularly noteworthy given the relatively limited number of available features and their seemingly disconnected relationship with the satisfaction status (with the exception of the delay feature). Despite this apparent lack of direct association, the models still achieved impressive performance, indicating their ability to uncover hidden patterns and capture relevant information from the available data. This finding underscores the robustness and effectiveness of the models in predicting passenger satisfaction, even in the absence of explicit indicators (like the direct feedback from passengers) or features directly linked to satisfaction.

Among the five algorithms tested, the Random Forest and Neural Networks stood out with comparable performance metrics. The Random Forest algorithm was selected to identify the crucial factors influencing passenger satisfaction. As depicted in Figure 22, the most important features for this model were found to be the passenger's Class and Type of Travel. Furthermore, the age was the third most important factor, however with a relatively lower importance compared to the first two factors. This result is in line with the decision tree model (Figure C – 1, Appendix C) in terms of the Class being the most important feature. However, in this last model, the Customer Type is the second most important factor.

In contrast, the model incorporating personal responses exhibited exceptional performance, as anticipated, with an average accuracy of 93%. Notably, both the Random Forest and Neural Networks models achieved the highest accuracy rates, with approximately 96% accuracy each (96.4% and 95.6%, respectively). Furthermore, the average F1-Scores and AUC across all five models were 0.92 and 0.97, reaffirming the substantial improvement in predictive capabilities when incorporating direct passenger feedback. These results highlight the significant impact of personal responses in enhancing the accuracy and reliability of the predictive models.

This time, the Random Forest algorithm was found to be the best one, across all the used metrics. Therefore, it was also used to identify the most important factors influencing passenger satisfaction. The most important factor (as seen in Figure 23) was the Inflight Wifi Service, closely accompanied by the Class. With a lower importance, the Type of Travel and Gate location are the third and fourth most important factors. Regarding the decision tree model (the worst of all the five algorithms tested), plotted in Figure C – 2 of the Appendix C, the most important factor was Online Boarding, followed by Inflight WiFi Service and the Type of Travel. Curiously, Online Boarding was the least important factor for the Random Forest algorithm.

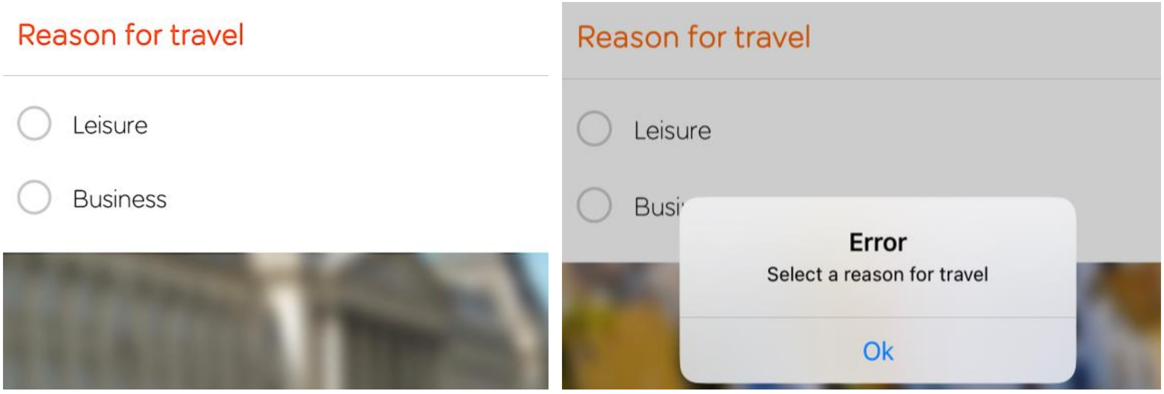
Comparing the results obtained with the test and train datasets, it is possible to observe that, as expected, the test dataset presents worse results than the training dataset. However, it is possible to conclude that the probability of having overfitting is very low since the differences between the two datasets are not large.

As all the models behave very well, there are no significant advantages of using the ensemble of the ML methods.

In practical terms, airlines that wish to apply ML models for passenger satisfaction prediction should begin by improving their systems to capture additional features during the booking process. For instance, on its mobile app, easyJet requires passengers to select the reason for travel (equivalent to Type of Travel, in this study), as seen in Figure 24.

Once the necessary data is obtained, airlines should test multiple algorithms and select the most suitable one, potentially even combining several models in an ensemble. The choice of the model, along with the corresponding evaluation metric, is at the discretion of the airline, based on their strategic objectives and the characteristics of the available data.

Figure 24 | "Reason for Travel" selection in easyJet mobile app



To illustrate this point, a scenario with a relatively balanced dataset can be considered. If the airline's goal is to simply send an apology email to unsatisfied passengers, using the accuracy metric would generally be enough. However, if the objective changes to offering a 30€ voucher exclusively to unsatisfied passengers, ensuring that the model accurately identifies only those passengers becomes crucial. In this case, the specificity metric would be the most appropriate, as it focuses on correctly identifying the true negative cases. By prioritizing specificity, the airline can be confident that the vouchers are provided to the intended recipients, avoiding potentially costly errors and ensuring customer satisfaction.

Once the appropriate model was designed, it can be deployed – which is, in basic terms, making it useable for final users (Humble & Farley, 2011). Then, for each flight, an automated system could pass to the model all the features for every passenger that was onboard that flight, and then return a list of unsatisfied passengers. Finally, for each dissatisfied passenger, the airline could send an email apologizing or send a voucher.

Additionally, there is also the possibility of combining approaches: for instance, the model outputs the probabilities of being satisfied, and the airline decides that it will offer a voucher if the probability is less than 15%, and an apology email if the probability is less than 60%. At the end of the day, the possibilities are endless, and each airline should decide and act according to its strategy.

From the passengers point of view, it conveys the message that even though they may be just one customer among millions, the airline still found a way to recognize and acknowledge their individual experience. By accurately identifying that they were dissatisfied, the airline demonstrated its genuine interest in addressing their concerns and ensuring their satisfaction. This personalized approach makes the passenger feel valued and reassured that the airline is committed to making their experience as positive and satisfactory as possible. It transmits a sense of trust and strengthens the airline reputation for customer focus and satisfaction.

Conclusion

The air travel industry has a significant importance for the global economy, playing a crucial role in promoting economic growth, connectivity, and facilitating international trade. It serves as an important bridge that connects people, businesses, and regions worldwide, enabling the easy flow of goods. By directly contributing to the GDP, as well as supporting related industries like tourism, manufacturing, and logistics, the aviation industry serves as a key driver of economic activity. Additionally, it drives innovation, technological advancements, and infrastructure development. The significant impact of the air travel industry on the global economy highlights the need to understand and address the industry challenges and decision-making processes.

Airlines play a significant role in the air travel industry, facing numerous challenges. However, like any other company, ensuring their customer's satisfaction remains a top priority. Extensive research has been conducted linking service quality to passenger satisfaction, exploring various dimensions such as seat comfort, punctuality, food and beverages, and baggage handling, among others. In fact, the literature reveals a lack of consensus among passengers and airlines regarding the factors that contribute to passenger satisfaction. This highlights the importance of recognizing that generalizations are rarely applicable, emphasizing the need for tailored strategies to address the specific needs and expectations of diverse passenger segments. Each airline must gain a deep understanding of its unique passenger base and adapt its strategies accordingly to achieve high levels of overall satisfaction.

Within this framework, the ability to predict passenger satisfaction is of particular importance, as a substantial part of passengers may not communicate their dissatisfaction to the airlines. Therefore, predictive models play a crucial role in identifying and addressing potential areas of dissatisfaction proactively. Moreover, understanding the contribution of each service dimension to passenger satisfaction becomes even more critical when airlines are designing their product and service offerings.

In the day-to-day operations of airlines, the key focus is on determining whether passengers were satisfied overall, rather than analysing the impact of individual variables on satisfaction. While there will always be both positive and negative aspects, understanding the overall satisfaction level is what matters the most. Therefore, this dissertation focused on creating predictive models for passenger satisfaction.

This study relied on a dataset that consisted of passenger responses to an airline survey. The survey encompassed both personal factors, such as opinions on seat comfort, Wi-Fi service, and baggage handling, as well as general factors like flight punctuality and distance. Each record of the dataset, representing a passenger, also contained a binary label of satisfied or neutral / dissatisfied. Two models were created: one using only general factors (also known as "without personal responses"), and the other including general factors and personal factors (also known as" with personal responses").

In comparison to random guessing, both models demonstrated remarkable predictive capability in determining passenger satisfaction. The models that did not incorporate personal responses exhibited an average accuracy of 79%, with F1-Scores and AUC averaging at 0.76 and 0.84, respectively. These results indicate that, even in the absence of explicit factors, it is still possible to accurately predict passenger satisfaction. Moreover, these findings highlight the ability of the machine learning algorithms utilized to uncover hidden patterns and establish connections between apparently unrelated variables.

The model incorporating personal responses achieved even higher performance, with an average accuracy of 93% and F1-Scores and AUC averaging at 0.92 and 0.97, respectively. In both models, the Random Forest algorithm emerged as the top performer, achieving an accuracy of 80.28% for the model without personal responses and 96.41% for the model with personal responses. These results highlight the positive impact of incorporating personal feedback from passengers regarding their satisfaction with various service dimensions on the predictive capability of the model. However, it is worth noting that the increase in performance compared to the model without personal responses was not as substantial as the improvement observed when comparing the latter to random guessing.

In terms of feature importance, for each model, the results were compared using Random Forest and Decision Trees. For the model without personal responses, the most important feature, for both algorithms, was the Class. In the model with personal responses, the most important feature was the Inflight Wifi Service (for the Random Forest Algorithm) and the Online Boarding (for the Decision Tree).

While the results of this study demonstrated the potential to predict passenger satisfaction with a significant level of accuracy, it is important to acknowledge certain limitations. Firstly, the findings are specific to the airline that was the focus of the survey, and it is possible that other airlines may yield different results due to variations in their service quality and passenger preferences. Secondly, the limited number of features in the model without personal responses may have impacted the overall predictive performance. Finally, the absence of hyperparameter tuning in the analysis may have limited the generalizability of the results to other passengers within the same airline.

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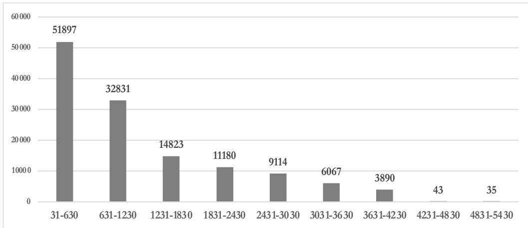
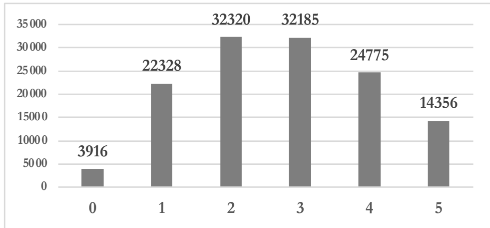
Appendix A | Distribution of the Dataset Features

Figure A - 1 | Distribution Plots of the Dataset Features

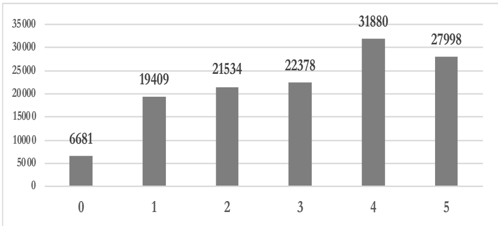
Flight Distance



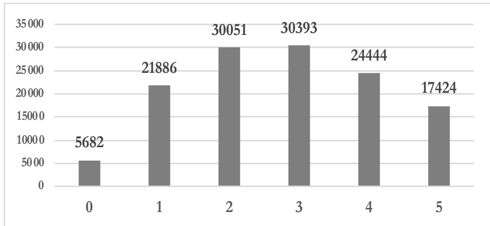
Inflight Wifi Service



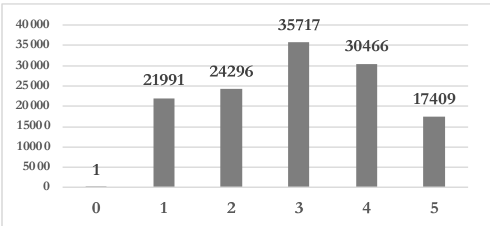
Departure/ Arrival Time Convenient



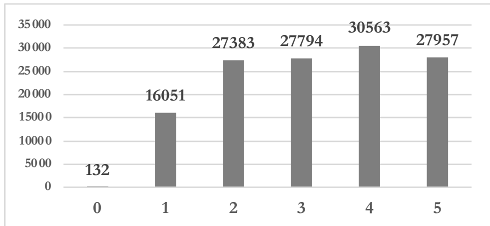
Ease of online booking



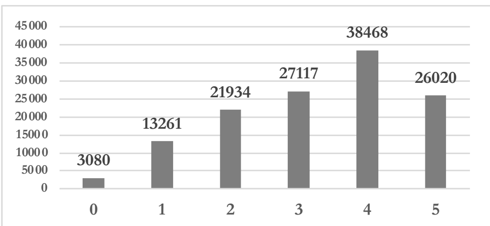
Gate Location



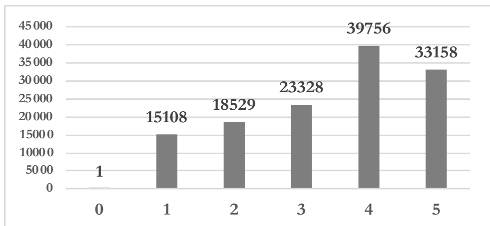
Food and Drink



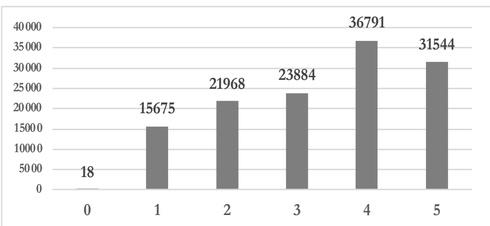
Online Boarding



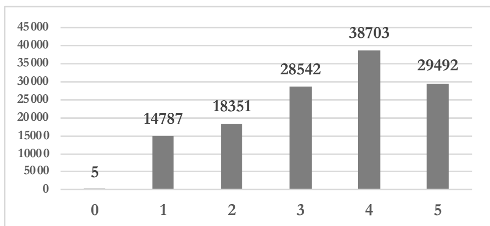
Seat Comfort



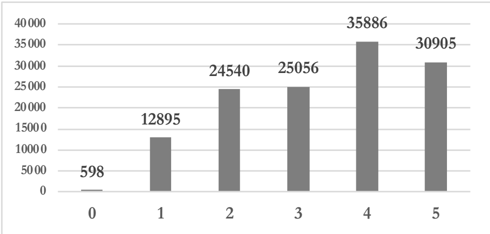
Inflight Entertainment



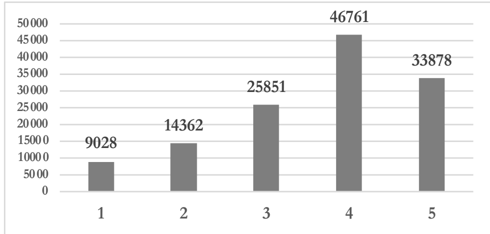
On-board Service



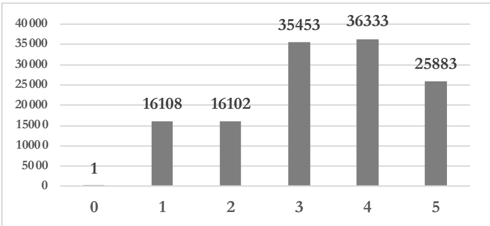
Legroom Service



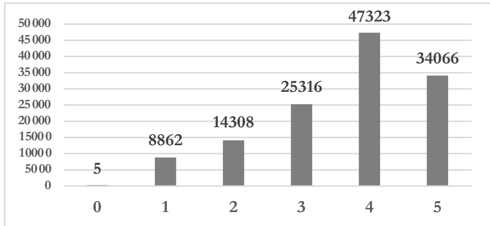
Baggage Handling



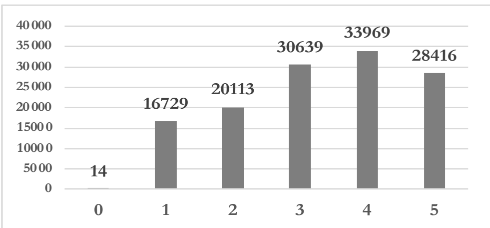
Check-in Service



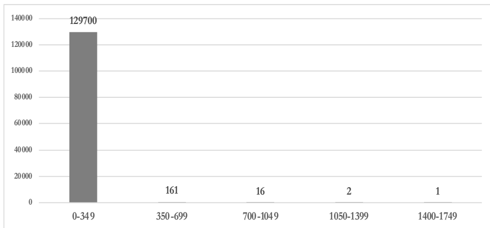
Inflight Service



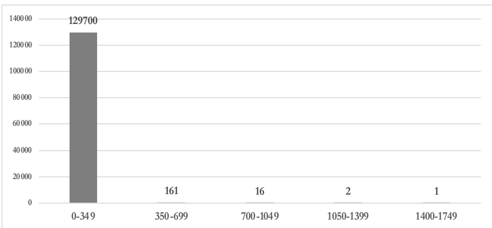
Cleanliness



Departure Delay in Minutes



Arrival Delay in Minutes



Appendix B | R Libraries Used

Table B - 1 | R Libraries Used

Libraries
`library(caret)`
`library(earth)`
`library(iml)`
`library(metan)`
`library(mltools)`
`library(pROC)`
`library(randomForest)`
`library(rpart)`
`library(rpart.plot)`
`library(rsample)`

Appendix C | Decision Trees

Figure C - 1 | Decision Tree of the model without Personal Responses

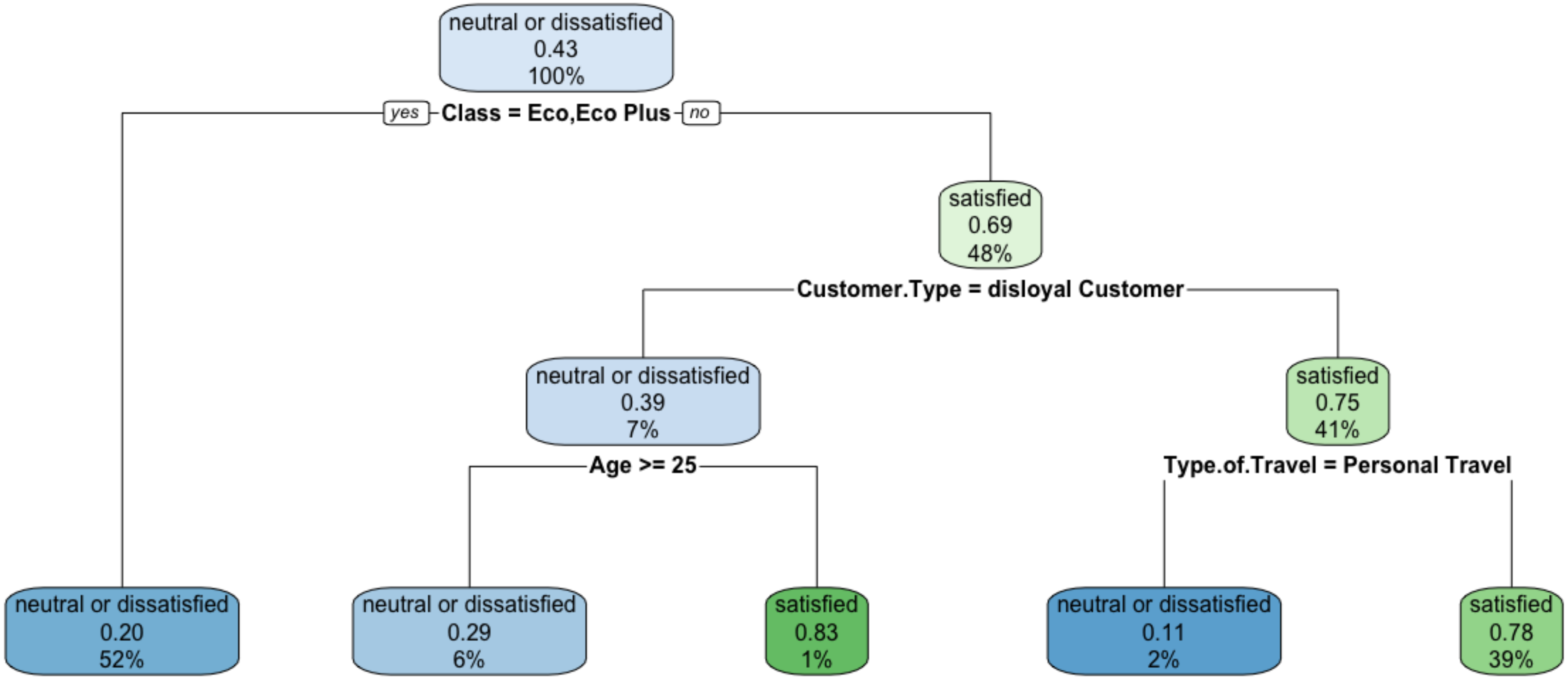


Figure C - 2 | Decision Tree of the Model with Personal Responses