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Improving Quality through Customer Feedback Analysis

Insights from Airline Reviews

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1. Introduction

The increasing availability of customer-generated data in the airline sector underscores the strategic importance of Customer Feedback Analysis for extracting insights and supporting data-driven decision-making processes. In industries where customer perception directly impacts brand reputation and profitability, such as aviation, understanding the evolving expectations and experiences of passengers has become a critical business priority. Airline operators must continuously monitor service quality across multiple touchpoints and within this context, customer reviews and feedback represent a valuable resource for improving service quality, enhancing customer experience, and maintaining competitive advantage.

This thesis focuses on evaluating airline customer satisfaction by leveraging review data collected over a nine-year period, from 2015 to 2023. The primary objective of this work is to develop a robust analytical tool, specifically, an interactive dashboard created with Microsoft Power BI, that facilitates a deeper understanding of passenger satisfaction and supports strategic quality management. By examining different dimensions associated to type of travelers, route categories, and aircraft models, the dashboard offers a multifaceted view of the elements that influence variations in the overall airline rating.

This project is designed to pass through both the theoretical and practical aspects of a customer feedback analysis applied to a real-life case, firstly introducing the foundations of customer feedback analysis within the framework of Quality Engineering, presenting key performance indicators (KPIs), the implications for decision-making roles, and the use of data visualization tools and then narrowing the focus to the aviation industry, exploring its unique feedback collection challenges.
The work performed focuses then on the analysis of the dataset used to develop the dashboard, detailing the data cleaning and preprocessing steps necessary to ensure accuracy and analytical relevance. This is preparatory for the discussion about the implementation of Power BI for dashboard development, offering a breakdown of the five main pages built to support both general and targeted analysis.

Once the development of the dashboard has been analyzed, the discussion moves on the in depth analysis, focusing on potential real-life situations in a company, beginning with the identification of temporal trends, through insights drawn from route-based and aircraft-based categorizations.
The temporal analysis revealed two critical declines in the overall rating, the first one in 2017 with a drop of 24% compared to the previous year, and a continued downward trend from 2020 to 2023, with year-over-year reductions of 8.5%, 12.4%, and 23.4%, respectively. These findings suggest both structural and contextual factors influencing customer perception over time. In terms of service parameters, “Value for Money” was

identified as one of the factors with the strongest impact on the overall rating for both the decrease in 2017 and in 2020.

From the 2017 analysis, it emerged that the insights derived from the dashboard are not only diagnostic but also predictive in nature. The areas identified as critical for improvement, such as the perceived value for money and aspects of cabin staff service, align closely with initiatives that were gradually implemented by airlines in the years that followed, such as the introduction of loyalty programs, more transparent fare structures, and personalized in-flight services, that reflect an industry-wide shift toward addressing weaknesses highlighted also in this project.
When considering the 2020 decrease it will be evaluated also how the outbreak of COVID-19 led to an unprecedented disruption of air travel worldwide and how essential it has been for airlines to pivot towards strategic reinvestment in the onboard experience, leveraging customer feedback to prioritize initiatives with the greatest impact on perceived quality, to rebuild trust and satisfaction in customers in order to improve the overall rating of the company.
From a strategic perspective, the route-based and aircraft-based analyses allowed for the identification of geographical and operational patterns, highlighting how customer perception varies based on route sensitivity and fleet composition. The route analysis identified high-performing regions that could serve as internal benchmarks for underperforming routes, and suggested that geographically stable routes could be used to test service improvements before large-scale implementation. Similarly, the aircraft model analysis revealed how customer feedback can be tied directly to fleet investment decisions, particularly where consistent underperformance was noted for specific aircraft types.
These analytical results not only allow for retrospective evaluation of customer sentiment but also help suggest corrective actions and service improvements.

After the quantitative analysis of the results obtained, the thesis proposes two key areas for future development: dynamic route categorization and aircraft classification by family. These enhancements are intended to address some of the limitations identified in the current model, and to suggest areas of improvements to make the dashboard developed more effective and in scope with companies needs.

In conclusion, this thesis demonstrates how advanced Customer Feedback Analysis, powered by Business Intelligence tools like Power BI. can transform static review data into dynamic, strategic insights. The resulting dashboard provides airline managers with an intuitive, real-time instrument for monitoring customer sentiment, identifying service weaknesses, and testing targeted improvements. Ultimately, it highlights the role of data visualization not just as a reporting tool, but as a driver of quality and innovation in customer focused industries.

2. Customer Feedback Analysis in Quality Engineering

In today's rapidly advancing world, the role of service quality has become extremely important to be competitive in the market and reach sustainability.
In the evolving landscape of modern industries, as businesses increasingly shift from product-centric to service-oriented paradigms, the ability to understand and meet customer expectations has become critical. High-quality service is no longer merely a differentiator, it is a prerequisite for customer loyalty and operational efficiency. Customer feedback, thus, emerges as a dynamic tool to monitor, assess, and improve the overall service experience.
This shift underscores the importance of customer feedback as a strategic resource for quality engineering, the discipline of engineering related to the implementation of systems that ensure products or services meet customer requirements, while fostering continuous improvement and instead of only looking for issues at the end, it focuses on embedding quality throughout the entire development process[1].

Customer feedback analysis fuels the continuous improvement cycle, known as the PDSA cycle[2] (Plan, Do, Check and Act) central to Total Quality Management (TQM) frameworks.
Originally derived from the scientific method and developed through the work of Walter A. Shewhart and later W. Edwards Deming, the cycle emphasizes structured experimentation and learning, as a path to process and product improvement.
The cycle begins with the "Plan" phase, where a problem is identified and a hypothesis is formed. Next, the "Do" phase involves implementing a test of the proposed change. In the study phase, formerly "Check", the results are analyzed against expectations. Finally, the "Act" phase determines whether to adopt, adjust, or abandon the tested change.
Integrating customer feedback into this model provides a powerful mechanism to detect failures, identify improvement opportunities, and adapt services to evolving expectations. By aligning the voice of the customer with structured quality improvement cycles, organizations ensure that change is not only continuous, but also meaningful and measurable.

Feedback mechanisms enable organizations to monitor performance, identify gaps, and drive innovation in services and operations. Customer Feedback Metrics, also known as CFMs, such as Net Promoter Score (NPS), Customer Satisfaction (SAT), and Customer Effort Score (CES) have become integral to the development of marketing and quality

[1] Nazneen Ahmad, *What Is Quality Engineering: Roles of a Quality Engineer*, Lambdatest, 13th of March 2025, https://www.lambdatest.com/learning-hub/quality-engineering, consulted on the 18th of June 2025.
[2] Moen, R. D., Norman, C. L. *The history of the PDCA cycle*, The Deming Institute, (2006), https://deming.org/wp-content/uploads/2020/06/PDSA_History_Ron_Moen.pdf consulted on the 19th of June 2025.

control strategies across sectors[3]. These metrics not only quantify customer sentiment but also act as early indicators of quality deterioration or unmet expectations. By embedding CFMs into quality engineering systems, firms can link technical process outcomes directly to customer centric objectives, transforming abstract feedback into actionable engineering insights. Continuous loops of feedback help firms to remain adaptive and responsive, enhancing their ability to retain customers and maintain operational excellence.

Feedback analysis has profound implications across various organizational roles. Quality managers rely on CFMs to assess compliance with service standards and prioritize improvement areas. Customer service managers use them to tailor interactions and training. Executives and strategic planners view feedback as an essential input into high-level decisions related to market positioning and resource allocation.
Research by Agag et al. (2023) demonstrates that firms aligning CFMs with financial indicators such as gross margin or sales growth achieve superior performance and investor confidence. Moreover, customer feedback helps differentiate firms in highly competitive markets by reinforcing a customer-centric culture.

When talking about a customer-centric culture, business organizations must also consider how customers form perceptions of products, services, and organizations based on a variety of individual and contextual factors. These include prior interactions, habitual expectations, and the usage environment, whether personal or professional. Research shows that customer expectations vary substantially between B2B and B2C settings[4], where motivations, goals, and service touch points differ (De Keyser et al., 2020; Meyer & Schwager, 2007, as cited in Luhtakanta, 2023). For example, professional users may prioritize reliability and performance, while consumer users might focus more on ease of use or emotional engagement. These distinctions are crucial for quality engineering, as the systems designed to collect and act on feedback must be flexible enough to reflect the diverse realities of the customer base.

(Becker and Jaakkola, 2020, as cited in Luhtakanta, 2023) have proposed eight distinct classifications of customer experience, ranging from retailing, consumer research, service-dominant logic, service design, branding, and online marketing, to service and experiential marketing, each highlighting a unique dimension of how quality is perceived and evaluated. For Quality Engineering, these categories offer valuable frameworks for contextualizing feedback data and translating abstract experiential

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[3] Agag, G., Durrani, B. A., Shehawy, Y. M., Alharthi, M., Alamoudi, H., El-Halaby, S., Hassanein, A., and Abdelmoety, Z. H. *Understanding the link between customer feedback metrics and firm performance*. Journal of Retailing and Consumer Services, July 2023, https://doi.org/10.1016/j.jretconser.2023.103301 consulted on the 19th of June 2025.

[4] A. Luhtakanta, *From Customer Feedback to Implemented Feature: Improving Customer Feedback Process Management*, M.S. thesis, Aalto Univ., Espoo, Finland, 29th of May 2023, https://aaltodoc.aalto.fi/server/api/core/bitstreams/387d891a-8e26-4a92-a544-9b81b46c99b7/content consulted on the 19th of June 2025.

responses into measurable quality indicators.
Once those frameworks have been identified, a key component in understanding customer experience is the concept of touchpoints, which represent the various interactions a customer has with the company throughout their journey. These include both direct and indirect contacts, such as visiting physical stores, making online purchases, speaking with service representatives, or reading customer reviews. Some touchpoints are within the organization's control, like the ambiance of a physical branch or the structure of customer service scripts. Others, such as peer recommendations or social media sentiment, fall outside direct influence. Importantly, businesses must resist the temptation to focus solely on isolated touchpoints, such as a single website interaction or a helpdesk exchange. Instead, customer experience should be understood as the collective experience across a network of touchpoints, connected through various channels and contexts.

In today's omnichannel environment, many companies operate across both physical and digital platforms, creating a range of possible flows in the customer journey. Quality Engineering must therefore consider how all these elements contribute to the total experience, and how customer feedback can be systematically collected, interpreted, and applied to optimize every dimension of interaction.

2.1 Key Performance Indicators (KPIs) in Quality Management

Modern customer feedback analysis is closely tied to the monitoring and interpretation of strategic Key Performance Indicators (KPIs), which serve as quantifiable metrics to assess and improve service performance. These indicators form a critical bridge between the customer's voice and the company's decision-making processes, enabling businesses to translate subjective customer perceptions into actionable insights.

A more in-depth look at the aforementioned KPIs, as outlined by Agag et al. (2023), provides a clearer understanding of their definitions and practical applications across various industries:

- Net Promoter Score (NPS), the metric that measures the likelihood a customer would recommend the evaluated service to others. Unlike other indicators that focus on present satisfaction, NPS is forward-looking and is often interpreted as a proxy for future customer behavior and loyalty. High NPS scores are strongly correlated with positive word-of-mouth, repurchase intentions, and overall brand advocacy. In B2C environments, for instance, NPS is a key benchmark for brand strength, while in B2B it can influence contract renewals and long-term partnerships. Agag et al. (2023) underline its widespread adoption in sectors such as e-commerce, hospitality, and telecom, where customer retention is a critical success factor.

- Customer Satisfaction (SAT), which is often collected through post interaction feedback, provides a snapshot of how well a service or product met customer expectations. Unlike NPS, which emphasizes future behavioral intent, SAT is experience based and immediate, making it a valuable tool for identifying short-term quality gaps and service inconsistencies. According to Agag et al. (2023), industries such as banking and telecommunications rely heavily on SAT to monitor service delivery at scale and calibrate employee performance or branch-level operations accordingly.
- Customer Effort Score (CES) evaluates how easy it was for a customer to complete a transaction or resolve an issue. CES focuses on efficiency and usability, making it particularly relevant in digital environments, customer support services, and self-service platforms. Lower effort scores are associated with higher loyalty, as customers increasingly expect seamless, frictionless experiences. CES is considered more retrospective than NPS, assessing past process design and service system effectiveness.

These three KPIs offer complementary perspectives: while NPS focuses on future intent, SAT captures present satisfaction, and CES reflects the past effectiveness of service delivery. When used collectively, they provide a comprehensive view of customer experience and operational performance.
Furthermore, their utility extends beyond descriptive reporting. When properly integrated into quality engineering and business intelligence systems, these KPIs can inform both tactical decisions, such as reallocating support resources or adjusting onboarding flows and strategic planning, including product development, market positioning, and brand management.

Importantly, as Agag et al. (2023) suggest, the impact of feedback metrics becomes most powerful when they are linked to financial and operational performance indicators. Organizations that successfully connect CFMs with outcomes like sales growth, gross margin, or customer lifetime value gain a competitive edge, as they are better equipped to prioritize initiatives that deliver measurable business value. This strategic alignment reinforces the role of KPIs as not just evaluative tools, but as drivers of continuous quality improvement and customer centric innovation.

Schmidt (2024)[5] explores how standardized Quality KPIs across production sites enable internal benchmarking, performance comparability, and strategic alignment. This standardization, when combined with business intelligence tools, allows firms to

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[5] Schmidt, Y., *Global standardization of Quality Key Performance Indicators: An Endress+Hauser Flowtec AG case study*, Master's thesis, KTH Royal Institute of Technology, 2024, https://kth.diva-portal.org/smash/get/diva2:1883212/FULLTEXT01.pdf, consulted on the 25th of June 2025.

integrate customer experience metrics into broader strategic decisions, ranging from process redesign to capital investments, while maintaining operational cohesion across geographies. Furthermore, Schmidt highlights how embedding these KPIs into manufacturing processes enabled management to identify inefficiencies, support root-cause analysis, and take targeted action to reduce production costs. By linking operational quality data with financial objectives, organizations are able to make more informed decisions that contribute to both performance optimization and economic efficiency. Notably, the linkage between customer-related KPIs and economic returns is not just implicit but actively measured and used to justify managerial actions.

Among the most strategically relevant customer and quality KPIs are the Cost of Poor Quality (CoPQ) and the Net Promoter Score (NPS), both of which have shown strong correlations with financial performance when systematically monitored and integrated into decision-making processes. CoPQ represents the cumulative cost associated with delivering products or services that do not meet quality standards, including internal failures (e.g., rework, scrap) and external failures (e.g., warranty claims, complaint handling). These hidden costs, if left unmanaged, can significantly erode profit margins. However, when tracked through a structured quality management system and visualized via business intelligence tools, CoPQ becomes a powerful lever for cost containment. Organizations that actively reduce their CoPQ through proactive quality interventions typically report notable gains in operating margins and resource efficiency.

On the customer side, NPS serves as a proxy for customer loyalty and future purchasing behavior. High NPS values are associated with stronger brand advocacy, higher retention rates, and increased customer lifetime value (CLV). Companies that monitor NPS in real time can adapt more quickly to shifts in customer perception, allowing them to adjust product offerings, service strategies, or communication efforts before dissatisfaction results in financial loss.

In this sense, the joint monitoring of CoPQ and NPS not only supports operational and customer-centric excellence but also enables measurable economic returns, from cost reduction to revenue growth, making them indispensable tools in the pursuit of sustainable business performance.

Similarly, Midor et al. (2020) demonstrate how tracking KPIs related to product defects and service delays allows manufacturing organizations to reduce non-conformance costs, improve responsiveness, and build customer trust[6]. In this study, the analysis of two primary KPIs, the quantitative complaint ratio, measuring the volume of customer complaints over total products delivered, and the qualitative complaint ratio, identifying

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[6] Midor, K., Sujová, E., Cierna, H., Zarebinska, D., & Kaniak, W., *Key Performance Indicators (KPIs) as a Tool to Improve Product Quality*, New Trends in Production Engineering, March 2020, http://www.stegroup.pl/attachments/category/93/10.2478_ntpe-2020-0029.pdf, consulted on the 25th of June 2025.

the most frequent defect types reported, allowed to isolate the main quality issue the company was facing, enabling the implementation of targeted corrective actions that led to a measurable reduction in complaints and associated costs.

To determine the root cause, the company implemented the 5 WHY methodology, a structured problem-solving technique used to trace operational failures by asking “why” iteratively until the fundamental source is revealed[7]. This led to the identification of gaps in process control and employee oversight. Based on the findings, the firm introduced several corrective measures: mandatory workstation checks before each shift, the implementation of employee bonus systems to encourage self-control, and improved maintenance protocols during production.
The outcome was twofold: first, the company experienced a significant drop in customer complaints, improving its product conformity rates and operational quality. Secondly, it realized tangible financial benefits through lower rework, warranty claims, and part replacements. The integration of well-targeted KPIs, focused on both frequency and nature of complaints, with root-cause methodology, not only improved responsiveness and internal accountability, but also strengthened customer satisfaction and reduced the Cost of Poor Quality (CoPQ). This case illustrates how feedback-based performance management, even in product-centric sectors, can directly support economic efficiency when quality indicators are actively monitored and acted upon.

These examples underscore that KPIs are far more than reporting metrics, they function as levers for cross-functional alignment and financial optimization. When customer feedback is translated into well-structured, quality-focused KPIs, and when those KPIs are tied to financial performance metrics, companies unlock a virtuous cycle of continuous improvement, customer loyalty, and business growth.

2.2 The impact of customer feedback analysis in business roles and decision-making

As already stated, customer feedback has evolved from a reactive support tool into a critical strategic resource that informs nearly every functional area of a modern business. The ability to systematically collect, interpret, and act on customer insights significantly influences organizational roles, decision-making processes, and competitive strategy, particularly in industries where customer experience plays a central role in value creation.

[7] Serrat O., *The Five Whys Technique*, Asian Development Bank, February 2009, https://www.adb.org/sites/default/files/publication/27641/five-whys-technique.pdf, consulted on the 25th of June 2025.

Across an organization, various roles are affected differently by feedback analysis, each contributing to its implementation and leveraging its outcomes to meet departmental objectives. Quality Managers rely heavily on customer feedback to identify defects, service delivery gaps, or unmet expectations. Through continuous analysis of customer feedback metrics, such as the ones aforementioned, quality managers are able to direct operational improvements, update service guidelines, and enforce compliance with internal quality standards. Feedback provides a direct connection between engineering performance and user experience, enabling data-driven enhancements to service delivery models.
Customer service managers use feedback to manage frontline performance, identify recurring complaints, and personalize support strategies. Real-time feedback tools empower these managers to deploy corrective actions quickly, such as updating knowledge bases or retraining agents based on customer pain points.
Marketing and strategy executives interpret feedback as a signal of brand health, campaign resonance, and product-market fit.

Particularly in dynamic industries, customer feedback plays a pivotal role in shaping marketing strategies, aligning with theoretical frameworks like the aforementioned Customer Feedback Loop, or more specific framework like Expectation-Confirmation Theory (ECT), and Service-Dominant Logic (SDL)[8].

The ECT provides valuable insights into the role of customer feedback, because it states that customer satisfaction is influenced by the confirmation or disconfirmation of prior expectations (Bhattacherjee, 2001, as cited in Mingjie & De Guzman, 2024). When advertising companies use customer feedback to align their marketing strategies with consumer expectations, they are more likely to achieve higher levels of satisfaction. This theory highlights the importance of understanding and managing customer expectations through continuous feedback and adjustment of marketing tactics.
SDL, as described by Vargo and Lusch (2016, as cited in Mingjie & De Guzman, 2024), emphasizes the co-creation of value between companies and customers, suggesting that feedback should be integrated into campaign development to tailor messages to evolving customer needs. A recent study in the advertising sector demonstrated that companies implementing structured feedback mechanisms are more capable of making iterative, data-driven improvements to campaign design and messaging, thereby maintaining relevance and competitiveness in rapidly evolving markets.

At the executive level, feedback trends are increasingly being integrated into high-level dashboards using tools such as Power BI, allowing C-suite leaders to monitor satisfaction, identify early signs of brand erosion, and anticipate shifts in consumer

[8] Mingjie, L., & De Guzman, G. R., *The role of customer feedback in shaping marketing strategies: Enhancing customer satisfaction in the advertising industry*. International Journal of Science and Engineering Applications, 2024, https://doi.org/10.7753/IJSEA1308.1009, consulted on the 19th of June 2025.

behavior. Strategic decisions, including new product launches, market entries, and pricing models, can be then evaluated in light of customer sentiment and experience data.

While customer feedback is broadly applicable, its strategic value is especially pronounced in industries where service quality and user interaction are core differentiators:

- Aviation: this industry uses feedback to monitor satisfaction across routes, aircraft, and service classes. Insights are used to adjust in-flight service offerings, allocate resources, and design passenger experiences that drive loyalty.
- Tourism and hospitality: guests reviews and satisfaction scores are central to hotel, cruise, and travel companies. Real-time monitoring of customer sentiment influences everything from room upgrades to customer loyalty programs.
- Retail and e-commerce: in fast-paced consumer markets, feedback analysis helps businesses identify failing products, improve online navigation, and address delivery concerns. Retailers increasingly rely on sentiment analysis and social listening to stay ahead of customer needs.
- Technology and software services: user experience feedback fuels agile development cycles. SaaS companies, for example, use CES and SAT scores to refine onboarding flows, enhance usability, and reduce churn.
- Advertising and media: as noted in recent industry research, structured feedback analysis is essential for tracking the performance of advertising campaigns and adapting them in real time. Agencies leveraging customer feedback loops remain more agile, ensuring message relevance and greater return on investment.

In all these industries, customer feedback is not merely evaluative, but it becomes a catalyst for innovation, personalization, and operational efficiency. When embedded across organizational roles, it enables cross-functional alignment, guiding both tactical responses and long-term strategic direction.

While the importance of customer feedback analysis is widely recognized in industries with direct consumer interaction, its role in less explored or traditionally product-centric sectors remains underdeveloped yet full of potential. Fields like manufacturing, logistics, healthcare technology, or B2B industrial services have historically prioritized operational efficiency, regulatory compliance, or technical performance over customer experience. However, as these sectors become increasingly digitized and customer expectations evolve, the integration of structured feedback mechanisms can offer significant strategic advantages.

In such contexts, customer feedback is not always as immediate or visible, yet it holds critical insights into long-term satisfaction, system usability, and service reliability. For example, in industrial automation or enterprise software, a seemingly minor usability issue reported by a small client segment could signal deeper design flaws that affect broader adoption. Similarly, in public services or infrastructure, citizen feedback can uncover inefficiencies or quality gaps not easily detected through standard KPIs.

A key challenge in these sectors lies in the collection and interpretation of relevant feedback, as customer relationships tend to be more complex, involve multiple stakeholders, and lack clear touchpoints. Therefore, applying Customer Feedback Analysis in these environments requires tailored methodologies, more qualitative approaches, and robust stakeholder engagement. Nevertheless, as markets become more competitive and customer centric models extend beyond traditional consumer industries, the ability to harness feedback effectively could become a differentiating factor even in the most operationally driven fields.

2.3 Data Visualization in feedback analysis: Power BI

The exponential growth of data in modern business environments has made data visualization an essential component of feedback analysis. As organizations collect increasing volumes of both qualitative and quantitative customer feedback, ranging from structured surveys to unstructured reviews and social media sentiment, the ability to synthesize and convert this data into actionable insight becomes a decisive competitive advantage. In this context, Microsoft Power BI has emerged as one of the most powerful and widely adopted business intelligence platforms for transforming raw data into dynamic, interpretable, and strategic dashboards.

Power BI enables businesses to connect disparate data sources, including CRM platforms, Net Promoter Score (NPS) tracking tools, post-interaction surveys, online review aggregators, and social sentiment platforms. Once connected, the tool supports real-time analytics, offering updated metrics on customer satisfaction, behavioral trends, and service performance across different segments. One of its most valued features is the ability to create interactive dashboards, allowing users to filter, segment, and explore data in ways that are tailored to their specific decision making roles.

Visual dashboards reduce the cognitive load associated with large, complex data sets and present insights in formats that are accessible across departments. For instance, quality engineers can rapidly detect performance dips in product support, while marketing teams can monitor the effectiveness of new campaigns based on real-time customer feedback. Executive teams, meanwhile, benefit from high-level overviews of satisfaction trends and performance anomalies, empowering them to align strategic priorities with emerging customer expectations.

In summary, Power BI empowers organizations to move beyond static reporting and toward continuous, visual, and interactive feedback monitoring, tailored to the diverse needs of modern enterprises. When properly embedded into quality engineering and service excellence frameworks, it not only enhances data accessibility, but also accelerates the feedback-to-action cycle, making it a critical enabler of modern, customer centric business practices.

3. Customer Feedback Analysis in the Aviation Sector

Although feedback analysis is valuable across all sectors, certain industries benefit more, due to the high touchpoints and variability in service delivery. The aviation industry, for instance, has made substantial progress in integrating passenger feedback into service improvements, from flight experience to customer support systems.

The aviation industry represents a unique and complex environment where service quality and customer satisfaction intersect with high capital investment, strict regulatory compliance, and a strong global competition[9]. Within this context, customer feedback analysis emerges as a critical strategic and engineering asset, with implications that involve areas of application from traditional marketing to support functions. Given the intensity of competition, increasing customer expectations, and a renewed post-pandemic focus on passenger experience, airlines and aircraft manufacturers alike are placing growing emphasis on the integration of structured feedback into their processes.

In the aircraft manufacturer sector, two notable systems for a more agile and customer centered approach, Virtual Customer Inspection (VCI) and Satisfaction-Importance Evaluation (SIE)[10], have been introduced to address the limitations of traditional post-delivery feedback loops.

Virtual Customer Inspection, is a digital solution based on Augmented Reality (AR) technologies such as Microsoft HoloLens. It allows airline customers to remotely inspect aircraft modules in a virtual 3D environment before physical construction is completed. This innovation enables real-time validation of configurations, and functional elements, giving clients a direct role in shaping the final design. From the manufacturer's perspective, VCI reduces the risk of costly rework and delays by enabling feedback to be addressed early in the production cycle. For the airline, it ensures that the delivered aircraft aligns more closely with operational expectations and customer service standards, enhancing satisfaction and brand consistency from the moment of entry into service.

Complementing this, the Satisfaction-Importance Evaluation model provides a structured analytical framework for prioritizing feedback. Drawing inspiration from tools such as the Kano Model and Quality Function Deployment (QFD), SIE evaluates each design attribute based on two dimensions: the importance of the feature to the customer and the level of satisfaction associated with it. By cross referencing these two

[9] Ma, X., *Enhancing Customer Satisfaction in the Airline Industry: A Case Study of Delta Airlines*. In *Proceedings of the 2nd International Conference on Financial Technology and Business Analysis*, 1st of December 2023, https://doi.org/10.54254/2754-1169/46/20230320 consulted on the 19h of June 2025.

[10] Gupta, R. K., Belkadi, F., Buergy, C., Bitte, F., Da Cunha, C., Buergin, J., Lanza, G., & Bernard, A. *Gathering, evaluating and managing customer feedback during aircraft production.* Computers & Industrial Engineering, 2018, https://doi.org/10.1016/j.cie.2017.12.012 consulted on the 19th of June 2025.

variables, manufacturers can systematically identify which features require immediate attention, particularly those with high importance and low satisfaction. The implementation of SIE supports evidence based design decisions and more efficient resource allocation during aircraft customization.

Together, VCI and SIE represent a strategic evolution in customer feedback integration. For manufacturers, they improve development timelines, reduce post-production modifications, and foster closer client relationships. For operators, they offer greater assurance that aircraft will be tailored to specific needs, operational, aesthetic, and experiential, resulting in improved performance and passenger satisfaction across the aircraft lifecycle.

3.1 Challenges in the customer feedback collection in the airline sector

Despite the strategic value of customer feedback in shaping service quality and operational improvement, collecting and utilizing feedback effectively in the aviation industry presents several unique challenges. These obstacles arise from the inherent complexity of the passenger journey and the diverse customer expectations.

One of the primary challenges lies in the fragmented nature of the air travel experience, which spans multiple service providers and phases, starting from the online booking and going through all that happens in the airport, the security checks, boarding, in-flight service, baggage handling, and post-flight support. Each of these stages may involve different entities (the airlines, airports and third-party contractors), making it difficult to assign responsibility for customer satisfaction issues. As a result, feedback collected at a specific point may not reflect the full experience or may be incorrectly attributed, limiting its value for root cause analysis.
Another challenge is the typically low response rate to customer surveys, especially those sent post-flight. Passengers often disregard follow-up emails or survey invitations, particularly for short-haul or routine flights. This introduces sampling bias, as feedback tends to be polarized, coming primarily from extremely satisfied or highly dissatisfied customers. As a result, the airline may miss insights from the “silent majority,” whose experience is neutral or slightly positive but still valuable for continuous improvement.
Lastly, there is often a tendency within airlines to focus feedback analysis on service related metrics, such as staff behavior or food quality, while underestimating operational frustrations such as long connection times, confusing airport layouts, or poor communication during delays. These operational pain points, although less visible in survey structures, often influence overall satisfaction more than soft service elements. Recognizing and addressing this bias is crucial for developing a balanced improvement strategy and to be able to intervene also in the improvement of operational inefficiencies.

In summary, collecting feedback in aviation requires thoughtful design and cross-functional integration to allow a valid and insightful collection of information. Addressing these challenges is essential for converting feedback into truly actionable insights, particularly in an industry where passenger experience is both a commercial differentiator and a reputational cornerstone.

3.2 Relevant KPIs in the Aviation Sector

In the aviation sector, Key Performance Indicators (KPIs) are essential tools not only for service quality tracking but also for operational safety and regulatory compliance. KPIs in aviation serve two interconnected purposes, measuring organizational performance and identifying areas that may pose safety risks or service deficiencies. Among the most frequently monitored KPIs[11] there are:

- Punctuality: on-time performance is a fundamental expectation for air travel. Delays or cancellations, even when caused by external factors such as weather or air traffic control, significantly affect customer satisfaction and airline reputation. This metric is directly linked to logistical coordination, fleet management, and maintenance reliability, for this reason it is quite difficult to intervene with measurable actions to improve it.
- In-flight service quality: this metric encompasses all services experienced during the flight, from cabin crew courtesy, seat comfort, food and beverage quality, cleanliness, and entertainment offerings. Unlike punctuality, which is operational, in-flight service involves both tangible and intangible elements. It is a key driver of overall satisfaction, especially on medium and long-haul routes, and is often evaluated through post flight surveys and third-party platforms.
- Baggage handling: luggage-related KPIs include lost baggage rates, delay frequency, and baggage delivery time at arrival.
- Overall experience: this metric is made of different KPIs, in fact can be measured via Net Promoter Score (NPS), Customer Satisfaction (SAT), or star ratings. This composite KPI encapsulates the customer's whole perception of the journey, from booking to check-in, boarding, flight, disembarkation, and post-flight service. It offers a strategic view into how all other factors combine to form brand perception and customer loyalty.

[11] Stu M., *What is a key performance indicator (KPI) in aviation SMS?* Aviation Safety Blog, 26th of April 2023, https://aviationsafetyblog.asms-pro.com/blog/what-is-a-key-performance-indicator-kpi-in-aviation-sms, consulted on the 19th of June 2025.

In conclusion, Key Performance Indicators in aviation serve as essential instruments for bridging operational efficiency with customer satisfaction. Their strategic role is not limited to internal performance monitoring, but also to translate customer feedback into measurable improvements, fostering more reliable and responsive operations.

4. Dataset description and Data Cleaning activities

To conduct the analyses presented in this thesis, a publicly accessible dataset was selected from Kaggle, an open-source online platform widely used for educational and research purposes. Kaggle functions as a collaborative environment that facilitates the sharing of datasets, analytical solutions, and insights across various disciplines, supporting both academic exploration and data science practice.

The decision to use a dataset from Kaggle was based on several factors. Firstly, the platform ensures a certain level of data quality and documentation, which facilitates understanding and preprocessing. Secondly, the already said open source accessibility of datasets, when used for academic and non-commercial purposes. Lastly, the community-driven nature of the platform often means that datasets come with useful comments, pre-processing scripts, and insights contributed by other users, which can be valuable for benchmarking and refining analytical approaches.

Moreover one of Kaggle's distinguishing features is its dataset badge system, which helps users identify the most valuable and trusted datasets based on community engagement. Datasets can receive Bronze, Silver, or Gold badges, depending on their popularity, quality, and usefulness as judged by user interactions such as downloads, votes, and comments. A Gold badge, the highest distinction, signifies that the dataset is widely appreciated for its completeness, reliability, and relevance.

The dataset[12] selected for this study holds a Gold badge, indicating a high level of quality and community endorsement. This distinction reflects its suitability for advanced analytical tasks and academic research.

The dataset chosen for this study relates to airline customer reviews and includes different variables that will be further analyzed in this chapter. Furthermore, the dataset covers a time span from 2015 to 2023, offering a solid and representative temporal range for analysis. This not only allows for the observation of trends over time, but also ensures that the data remains relatively recent and relevant to current industry dynamics.

4.1 Data overview

The dataset used in this study provides a comprehensive collection of customer reviews related to British Airways flights. Each entry corresponds to a single passenger's feedback and includes both qualitative and quantitative information, enabling a

[12] Data downloaded at this link https://www.kaggle.com/datasets/chaudharyanshul/airline-reviews/data, on the 7th of November 2024

multifaceted analysis of the travel experience. The dataset is structured to capture different aspects of the flight journey, from general impressions to specific service components.

Below is an overview of the all the variables collected in the dataset:

- Overall rating: a numerical score reflecting the customer's overall satisfaction with the flight experience. The score is expressed with numbers on a scale from 1 to 10;
- Review header: the title or headline of the customer's review, summarizing their general sentiment. The format of this data is a string;
- Name: the name of the individual submitting the review. The format of this data is a string. The answers structure is not unique because some present both name and surname in long form, while others only the initial of the name and the surname in long form;
- Datetime: the exact date when the review was published on the platform. The format of this data is a date (day, month and year);
- Verified review: a boolean (true/false) field indicating whether the review has been verified for authenticity;
- Review body: the detailed written feedback provided by the customer, containing qualitative insights into their experience. The format of this data is a string;
- Type of traveller: the traveler's profile type, providing context for their expectations and priorities. The format of this data is a string. The origin of the review form is not provided, but it is easy to suppose that this data was collected through single choice menu among the following options:
    - Business;
    - Couple Leisure;
    - Solo Leisure;
    - Family Leisure.
- SeatType: the class of travel selected by the customer, providing context for their expectations and priorities. The format of this data is a string. As previously written, the origin of the review form is not provided, but it is easy to suppose that this data was collected through single choice menu among the following options:
    - Economy;
    - Business Class;
    - First Class.
- Route: the origin and destination of the flight, giving geographical context to the feedback. The format of this data is a string. This data presents no unique structure, but a pattern has been recognized. In general the information is expressed through the name of the origin city, a conjunction between "to" or

"via" and the name of the destination city. In some cases the name of the city is followed by the airport code. In the following chapter it will be explained which activities have been performed to allow the analysis of this data;
- Date flown: the date on which the flight took place, as reported by the customer (date and year);
- Seat comfort: a rating specifically focused on the comfort level of the seating. The score is expressed with numbers on a scale from 1 to 5;
- Cabin staff service: a score reflecting the quality of the service provided by the cabin crew. The score is expressed with numbers on a scale from 1 to 5;
- Ground service: a score reflecting the quality of the services encountered on the ground, such as check-in or boarding assistance. The score is expressed with numbers on a scale from 1 to 5;
- Value for money: a score reflecting the customer's perception of whether the service received was worth the cost paid. The score is expressed with numbers on a scale from 1 to 5;
- Recommended: a binary (yes or no) indicator of whether the customer would recommend the airline to others;
- Aircraft: the model or type of aircraft used for the flight, where available. As already stated, the origin of the data is unknown, but it is possible to suppose that the information about the aircraft has been added in a second part of the enrichment of the dataset, because it is information not usually available to customers;
- Food and beverages: a score reflecting the quality and variety of food and drinks served on board. The score is expressed with numbers on a scale from 1 to 5;
- Inflight entertainment: a score reflecting the availability and quality of entertainment options during the flight. The score is expressed with numbers on a scale from 1 to 5;
- Wifi and connectivity: a score reflecting the quality of the onboard internet connection and related digital services. The score is expressed with numbers on a scale from 1 to 5.

This wide range of variables allows for a rich and detailed analysis, combining structured numerical ratings with unstructured textual data. Such a dataset enables the exploration of customer satisfaction from multiple angles, including traveler segmentation, route segmentation and service performance evaluation.

4.2 Data Processing Techniques

Before proceeding with the actual analysis and the development of the Power BI dashboard, several essential data cleaning procedures were carried out on the dataset.

Raw data often exhibit a range of imperfections, such as missing values, duplicate records, inconsistent formatting, and outliers, all of which can significantly distort analytical outcomes. If not properly addressed, these issues may lead to biased insights, reduced model accuracy, and, ultimately, undermine the validity of the entire study. Data preprocessing thus constitutes a critical step in the data analysis pipeline, as it directly influences the overall quality and reliability of the results obtained.

The preprocessing phase in this study focused on two key activities:
1. Handling missing data;
2. Conversion of data.

Each of these activities was performed systematically to enhance the dataset's consistency and usability. Specific strategies were employed based on the nature of the variables involved, balancing the need to preserve as much original information as possible with the necessity of maintaining a clean and coherent dataset structure.

4.2.1 Handling of missing data

The initial database contained a total of 3701 records. The deletion of some records has been performed in order to handle missing data.
All the records that presented at least one missing data for one of the following column of the dataset were deleted:
- Overall rating;
- Type of travel;
- Seat type;
- Route;
- Date flown;
- Seat comfort;
- Cabin staff service;
- Ground service;
- Value for money;
- Recommended.

The consequent reduction of records brought to a total loss of 915 records, equivalent to almost 25% of the total dimension of the dataset, down to 2786 records in total.

After this first cleaning activity to manage missing information from the previously indicated columns, some records still presented missing information related to the following columns:
- Aircraft;
- Food and beverage;
- Inflight entertainment;

- Wifi and connectivity.

Records containing missing values in the "aircraft" column were not removed from the dataset. This decision is justified by the fact that, as previously discussed in this work, the origin of the data is not fully traceable, and it is likely that the "aircraft" column was added at a later stage, subsequent to the initial data collection process.
Eliminating all records with missing aircraft information would have reduced the dataset to a total of 1897 entries, resulting in the loss of approximately 49% of the available data. Such a substantial reduction was deemed unacceptable, given the relevance and analytical value of the information associated with the affected records.
To manage the missing values in the "aircraft" column, the chosen approach was to replace the empty cells with the label "N/A," indicating that the information is not available. In subsequent analyses, these records will be categorized under the label "Various aircrafts."

A similar rationale was applied in addressing the missing information in the columns "Food and beverage," "Inflight entertainment," and "Wi-Fi and connectivity." The nature of these service categories suggests that they are typically relevant for long-haul flights or specific seat classes. However, not all flights included in the dataset meet these criteria. Consequently, the absence of data in these columns is not necessarily indicative of data quality issues, but may instead reflect the inapplicability of certain services to specific flights.
If all the records with missing data for one of these columns were deleted, the total amount of records will drop to 547 records, with a consequent loss of information of more than 85% of the total amount of records in the dataset.
Based on that, these missing data were intentionally left empty rather than being removed or imputed. This choice was made to avoid introducing distortions in subsequent calculations while also minimizing the loss of potentially valuable information.
A more detailed and sophisticated handling of these missing values will be discussed in the chapter dedicated to future developments of this work.

4.2.2 Conversion of data

Data conversion represents a crucial step in the preprocessing pipeline, especially when preparing a dataset for comparative analysis. In its raw form, data may be stored in different formats, scales, or structures that can obstacle straightforward comparisons or aggregations. Without proper conversion, inconsistencies between data entries could lead to analytical errors, misinterpretations, or difficulties in visual representation.

In this study, one variable was converted to ensure that all data points could be compared consistently and coherently. These transformations allowed for a more accurate alignment of the information across different dimensions, facilitating both the statistical analysis and the creation of clear and meaningful visualizations.

In fact, overall rating scores were given in a scale from 1 to 10, while all the others columns on a scale from 1 to 5. This caused a difficulty in comparing overall rating with the score of the single voice evaluated by customers and also in the interpretation of the impact of each variable on the overall score given by the customer.
For this reason overall rating scores have been converted into a scale from 1 to 5, to improve consistency.

Following the completion of the data cleaning and conversion activities, the dataset reached a level of consistency, completeness, and structural integrity suitable for advanced analysis. The preprocessing steps ensured that the data was free from major inaccuracies, formatted uniformly, and ready for integration into analytical tools.
At this stage, the dataset was ready to be imported into Power BI, where a further structuring to implement the analysis will be performed.
The careful attention given to the preprocessing phase was critical in ensuring that the analyses performed in Power BI would be both accurate and meaningful, providing a solid basis for data-driven conclusions.

5. Application of Power BI in dashboard development for customer feedback analysis

Upon completion of the data preprocessing phase and verification of the dataset's consistency and integrity, the subsequent step focused on the development of a series of interactive dashboards using Power BI. This chapter outlines the methodology adopted for the design and implementation of these dashboards, which were specifically developed to support the analysis of customer feedback data in an effective and user-friendly manner.

The primary goal of this phase was to create an analytical environment capable of presenting complex information in a simple, intuitive, and visually engaging way. Power BI was chosen for its powerful data modeling capabilities, its flexibility in managing different types of visualizations, and its ability to provide dynamic, real-time interactions with the data. These features made it possible to build dashboards that not only display information but also support deeper exploration and interpretation of customer behaviors.

Throughout the development process, particular attention was paid to ensuring that the design choices were always aligned with analytical objectives. The selection of appropriate visualization types (such as bar charts, line graphs or pie charts) was guided by the nature of the variables and the type of insights that were intended to be extracted. In parallel, specific data transformations and calculations were carried out directly within Power BI, through DAX formulas, Data Analysis Expressions, a specialized expression language used to define custom calculations and create dynamic measures, to further enrich the analytical depth and make certain variables more accessible and interpretable.

Moreover, a strategic use of filters, slicers, and drill-down functionalities was implemented to allow users to interact dynamically with the data, enabling multilevel exploration - from an aggregated overview down to more granular details. The dashboards were thus designed not only as static reporting tools but as flexible platforms for exploratory data analysis.

In summary, this chapter illustrates how Power BI was used to translate raw customer feedback into meaningful visual narratives, highlighting the analytical reasoning behind each development choice. The aim was to create dashboards that are capable of supporting effective decision-making processes based on clear, data-driven insights.

5.1 Importing and preparing data in Power BI

To ensure continuous accessibility of the dataset, the database was first uploaded to Microsoft OneDrive, a cloud storage service offering seamless integration with Power BI. For the nature of this specific project and more in general for what regards customer feedback analysis, data spans a defined historical period, so the need for dynamic updates was minimal, because the primary goal is to derive insights from an existing dataset rather than continuously monitor live data streams.

The connection between OneDrive and Power BI was established starting with the uploading of the dataset to One Drive, where it was then cleaned and processed. The dataset was saved in a structured Excel file format (.xlsx), making sure that every variable in the dataset was saved as the correct data type.
The dataset stored on OneDrive was then connected to Power BI creating a new report in the workspace and choosing the option of connecting through a file path or URL. This process imports the dataset as a Semantic Model, which contains the tables of data and will then also contain the relationship among tables, new columns created and DAX formulas. The Semantic Model is directly connected to the report where analysis can be further implemented.

Once the dataset is connected to Power Bi, the structure of the report was set up, with the goal of ensuring a clear navigation among the data and the results obtained with the analysis.

The organization of the pages follows a logical analytical flow, designed to guide users from a general overview of the data to more detailed, category-specific insights. This approach allows for a progressive exploration of customer feedback, facilitating both high-level understanding and in-depth analysis.

The first page, titled "General Data", provides a comprehensive summary of the dataset's overall distribution. It focuses on how reviews are spread across the reference years (from 2015 to 2023), offering temporal context to the analysis. This page serves as a starting point, helping users orient themselves with the available data and understand its scope and structure before diving into more specific metrics. Moreover it gives a picture of the quantity of data analyzed, important to understand reliability of the results obtained.
The second page, titled "Overall Rating", narrows the focus to the overall judgment given by customers to the airline. Here, the average rating is analyzed across key categories that help explain customer satisfaction, how it changed over time, related to different routes, aircraft categories and especially which aspects appear to have the greatest influence on the score feedback.
Lastly, the third page called "Analysis by Category" provides a comparative overview of customer feedback across two key dimensions: Route Category and Aircraft Type.

The page aims to highlight how passengers evaluate different aspects of their flight experience, based on the score collected for the different variables in the review form.

Importantly, all report pages include interactive filter panels, which allow users to dynamically adjust the scope of the analysis based on specific needs or areas of interest. This ensures that the report is adaptable and useful for various analytical purposes, from strategic decision-making to operational improvements.

Overall, this structure supports a balanced combination of exploratory and explanatory analysis, ensuring that both general trends and specific customer experiences can be easily interpreted and leveraged to extract meaningful insights.

5.2 Analysis of "General Data" page of the dashboard

The development of the dashboard starts with the "General Data" page, where comprehensive information about the dataset is shown.

Firstly, in figure 5.2.1 it is shown the line chart titled "TOT # of reviews by Year", which visualizes the temporal trend of reviews collected from 2015 to 2023. This chart provides an immediate understanding of how the volume of feedback has changed over time. On the x-axis is visible the year of reference, while on the y-axis the total number of reviews.
In order to obtain this result on Power BI, the line chart type of visualization was chosen, the variable "Datetime" from the dataset was inserted in the x-axis, choosing the "Year" as reference period, in order to have a clear and simple display of the trend.
The variable "Name" from the dataset was inserted in the y-axis. Thanks to Power BI functionalities, the count of the number of records for that specific year was selected directly in this section when creating the graph.

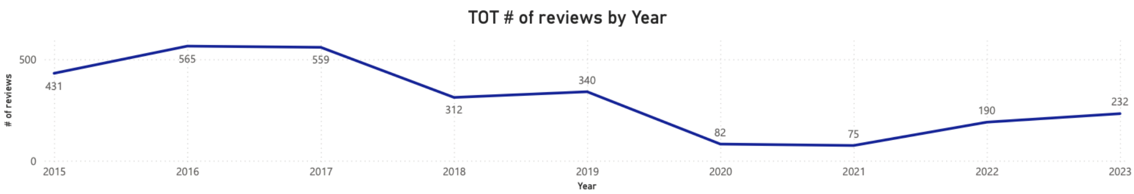

Figure 5.2.1 - TOT # of reviews by Year

In the graph it is possible to detect a steady increase in the number of reviews until 2017, when the number of reviews peaked, followed by a significant drop starting in 2018, and particularly evident in 2020 and 2021. This decline likely reflects the global reduction in air travel caused by the COVID-19 pandemic. A slight recovery is visible in the following years, showing a partial resurgence in passenger engagement.

In figure 5.2.2 are shown two Key Performance Indicators (KPIs), the total number of reviews and the average of the variable “Overall Rating”. Those two KPIs are shown through a card visualization, which allows to display different calculations based on the type of data which is inserted in the field. The card “TOT # of reviews” shows the count of the variable “Name” in the dataset, while the card “Average of OverallRating” shows the average calculated based on the score of the “Overall Rating” variable in the dataset.

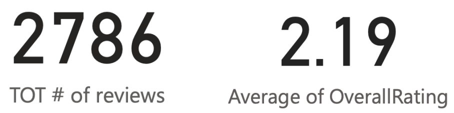

Figure 5.2.2 - TOT # of reviews & Average of OverallRating

The average rating, equal to 2.19, provides a quick measure of the overall sentiment expressed by travelers, one that is notably low on a typical five-point scale, further confirming the predominance of critical or negative feedback that will be visible also in the net promoter score graph.

In figure 5.2.3 is shown a pie chart titled "Verified Reviews", which presents the proportion of reviews marked as verified versus those that are not. This distinction is helpful to understand the level of authenticity within the dataset.
In order to create this graph, the pie chart of visualization was chosen, inserting the variable “Verified Review” of the dataset in the legend and the count of the variable “Name” in the value section.

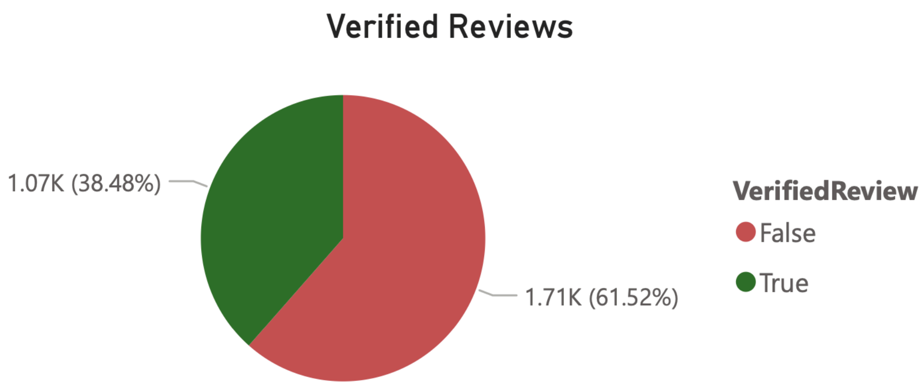

Figure 5.2.3 - Verified Reviews

In this case, the majority of the reviews are not verified (61.52%), indicating that a considerable portion of the feedback might come from users who have not been authenticated by the platform through which reviews have been collected.

In figure 5.2.4 is shown a pie chart titled “NET Promoter Score”, which shows distribution of responses to the question of whether the reviewer would recommend the airline. This chart offers a high-level view of customer loyalty and satisfaction.
In order to create this graph, the pie chart of visualization was chosen, inserting the variable “Recommended” of the dataset in the legend and the count of the variable “Name” in the value section.

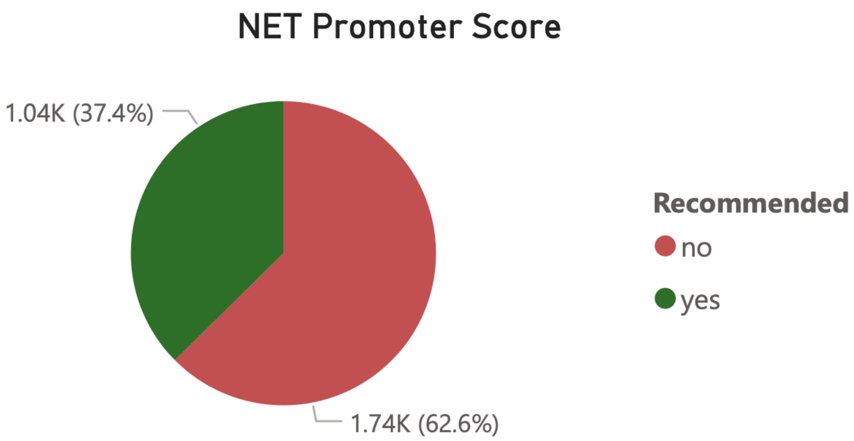

Figure 5.2.4 - NET Promoter Score

In the dataset, most users (62.6%) responded negatively, suggesting a general tendency toward dissatisfaction among travelers, or at least a limited inclination to recommend the airline.

In figure 5.2.5 is shown a bar chart titled “# of reviews by Traveller”, which breaks down the volume of feedback according to the type of traveler. Each bubble corresponds to a type of traveller, shown on the x-axis, and the dimension highlights the number of reviews for each category, whose count is shown on the y-axis.

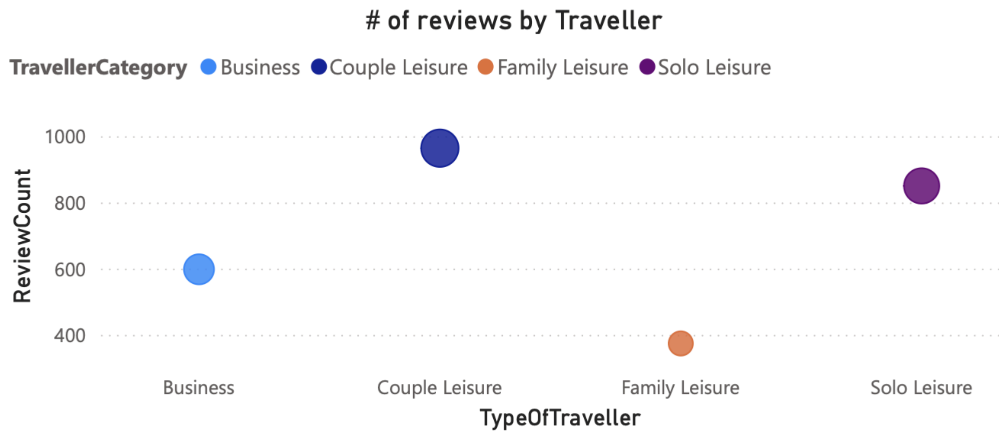

Figure 5.2.5 - Number of reviews by Traveller

The chart shows that the most active segments are "Couple Leisure" and "Solo Leisure," followed by "Business" travelers. This segmentation allows understanding which customer profiles are most represented in the data and potentially more influential in shaping the insights, because this also gives a picture of the most frequent type of travellers that use the service of the airline.

Finally, in figure 5.2.6. is shown a bar chart titled "# of reviews by Seat Type" a bar chart that displays how reviews are distributed across travel classes, such as Economy Class, Business Class, First Class, and Premium Economy. On the x-axis is shown the seat type while on the y-axis the count of the number of reviews for each type of seat.

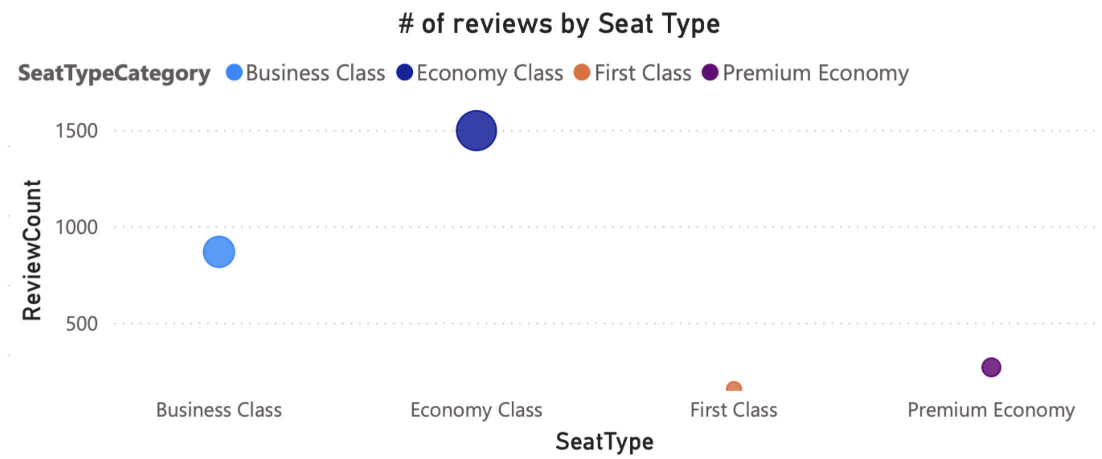

Figure 5.2.6 - Number of reviews by Seat Type

The chart reveals that Economy Class passengers submitted the largest number of reviews, likely reflecting the broader availability and usage of this class. This segmentation is critical for understanding whether satisfaction levels vary significantly depending on service class, but also how the perception of the service changes based on the type of ticket purchased by the client.

Together, these visual elements serve to contextualize the dataset by offering a multi-dimensional overview of its structure, distribution, and underlying sentiment, setting the foundation for more detailed analytical analysis in the following pages of the report.

5.3 Analysis of "Overall Rating" page of the dashboard

After the "General Data" page of the dashboard, the "Overall Rating" page gives a comprehensive picture of how the overall rating of the airline is influenced and connected with different relevant aspects, specifically the route and the aircraft. This page will help identify trends and drivers of satisfaction or dissatisfaction. Moreover it will be possible to analyze the results of the feedback filtering by the different characteristics of travelers.

In figure 5.3.1 is shown a line chart titled "Average of Overall Rating by Year" which tracks how the average overall rating has evolved from 2015 to 2023. The chart is obtained by inserting "Datetime" on the x-axis and specifically "Year" as reference period, while on the y-axis the value of the average of the "Overall Rating".

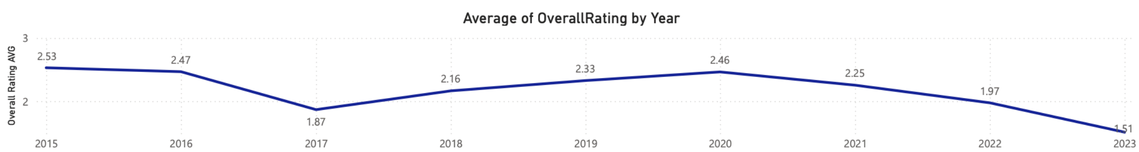

Figure 5.3.1 - Average of Overall Rating by Year

While the rating starts off moderately positive in 2015 at 2.53, a clear downward trajectory emerges over time, with a sharp drop in 2017, a brief recovery in 2019 and 2020, and then a continued decline, reaching its lowest point of 1.51 in 2023. This trend is in line with the result of the average of overall rating as seen in the card visualization in figure 5.2.2.
This chart paints a concerning picture of steadily decreasing passenger satisfaction over the years, potentially reflecting growing discontent with service quality or the impact of external events like the pandemic and operational changes, highlighting in particular

that the improvement activities that have been implemented, if any, have not led to improvements.

In figure 5.3.2 is shown a bar chart titled "Number of reviews by Route", which provides a distributional view of reviews based on the categorization of the route performed by the aircrafts. The chart is obtained by inserting on the x-axis the count of reviews, while on the y-axis the route category, a classification obtained through a DAX formula that will be now explained.

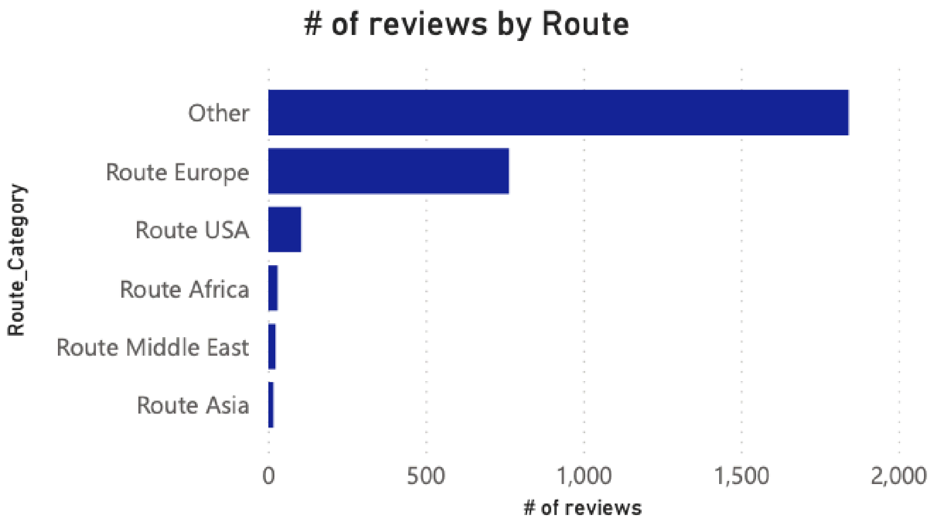

Figure 5.3.2 - Number of reviews by Route

In Power BI, DAX (Data Analysis Expressions) is the native formula language used to create custom calculations on data models. DAX allows to define calculated columns, measures, and calculated tables, enabling more sophisticated and dynamic data analysis beyond what is available in raw datasets. In the specific case of this thesis work, DAX formulas were written directly in the Data view. This functionality is particularly useful for data transformation and classification, where users need to derive new fields based on existing text, numerical, or categorical data.

In the case of the "Route_Category" field, a new calculated column was created, by a formula that evaluates the column "Route" row by row across the dataset. At the end, the result of the analysis is stored as a new column that can be used like any other field in the model.

In code 5.3.1 is shown the formula used to obtain the new column "Route_Category". The objective was to enhance the quality and clarity of the analysis, because the original "Route" column was not normalized: it consisted of free-text strings describing flight paths in varying formats, making it difficult to aggregate or compare routes effectively across the dataset.

To address this limitation, it was necessary to cluster the data into broader and more meaningful categories. The chosen approach was to classify each route based on its geographic area, focusing on the main regions served by the airline. Specifically, routes were grouped into five major categories: Europe, United States, Asia, Africa, and the Middle East. These clusters were defined by identifying key cities and international airports that typically appear at the origin or destination of a route. Routes that did not match any of these predefined geographic clusters were grouped under a catch-all category labeled "Other".

This classification not only improved the consistency of the data, but also enabled more focused and insightful comparative analysis of passenger satisfaction and review patterns across different regions.

```
Route_Category =
VAR RouteString = BA_AirlineReviews[Route]
VAR SearchPosition = SEARCH("to", RouteString, 1, 0)  -- Find position of "to"
VAR FirstCountry = IF(
   SearchPosition > 0,
   LEFT(RouteString, SearchPosition - 1),  -- Takes the string portion before “to”
   RouteString  -- If "to" is not found, returns the whole string
)

RETURN
SWITCH(TRUE(),
   // Route USA
   SEARCH("New York", FirstCountry, 1, 0) > 0 ||
   SEARCH("John F. Kennedy International Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("LaGuardia Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Newark Liberty International Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Los Angeles", FirstCountry, 1, 0) > 0 ||
   SEARCH("Los Angeles International Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Chicago", FirstCountry, 1, 0) > 0 ||
   SEARCH("O'Hare International Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Miami", FirstCountry, 1, 0) > 0 ||
   SEARCH("Miami International Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Dallas", FirstCountry, 1, 0) > 0 ||
   SEARCH("Dallas/Fort Worth International Airport", FirstCountry, 1, 0) > 0,
   "Route USA",
   // Route Europe
   SEARCH("London", FirstCountry, 1, 0) > 0 ||
   SEARCH("Heathrow Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Gatwick Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Paris", FirstCountry, 1, 0) > 0 ||
   SEARCH("Charles de Gaulle Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Orly Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Frankfurt", FirstCountry, 1, 0) > 0 ||
   SEARCH("Frankfurt Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Rome", FirstCountry, 1, 0) > 0 ||
   SEARCH("Leonardo da Vinci-Fiumicino Airport", FirstCountry, 1, 0) > 0,
   "Route Europe",
   // Route Middle East
   SEARCH("Dubai", FirstCountry, 1, 0) > 0 ||
   SEARCH("Dubai International Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Doha", FirstCountry, 1, 0) > 0 ||
   SEARCH("Hamad International Airport", FirstCountry, 1, 0) > 0 ||
   SEARCH("Riyadh", FirstCountry, 1, 0) > 0 ||
   SEARCH("King Khalid International Airport", FirstCountry, 1, 0) > 0,
```

```
    "Route Middle East",
    // Route Asia
    SEARCH("Tokyo", FirstCountry, 1, 0) > 0 ||
    SEARCH("Haneda Airport", FirstCountry, 1, 0) > 0 ||
    SEARCH("Narita International Airport", FirstCountry, 1, 0) > 0 ||
    SEARCH("Beijing", FirstCountry, 1, 0) > 0 ||
    SEARCH("Beijing Capital International Airport", FirstCountry, 1, 0) > 0 ||
    SEARCH("Shanghai", FirstCountry, 1, 0) > 0 ||
    SEARCH("Shanghai Pudong International Airport", FirstCountry, 1, 0) > 0 ||
    SEARCH("Hong Kong", FirstCountry, 1, 0) > 0 ||
    SEARCH("Hong Kong International Airport", FirstCountry, 1, 0) > 0,
    "Route Asia",
    // Route Africa
    SEARCH("Johannesburg", FirstCountry, 1, 0) > 0 ||
    SEARCH("O.R. Tambo International Airport", FirstCountry, 1, 0) > 0 ||
    SEARCH("Cape Town", FirstCountry, 1, 0) > 0 ||
    SEARCH("Cape Town International Airport", FirstCountry, 1, 0) > 0 ||
    SEARCH("Nairobi", FirstCountry, 1, 0) > 0 ||
    SEARCH("Jomo Kenyatta International Airport", FirstCountry, 1, 0) > 0,
    "Route Africa",
    // Default
    "Other"
)
```

Code 5.3.1 - Route_Category column

The logic behind the formula is as follow:

1. Variable Declaration. The formula begins by creating two variables, the “RouteString” which retrieves the current value in the “Route” column. The “SearchPosition” which uses the SEARCH function to locate the position of the word "to" in that string. This is used to identify the separation between origin and destination.
2. Extracting the Origin. Based on the position of "to", the formula extracts the substring preceding it using the LEFT function. This portion, referred to as “FirstCountry”, is assumed to represent the departure city or airport. If the word "to" is not found, the entire string is used as the origin, ensuring fault tolerance for any inconsistent formatting.
3. Route Classification. The main logic is a large SWITCH statement that evaluates a series of boolean conditions. For each geographic region the formula checks whether the “FirstCountry” string contains certain keywords, specifically the names of major cities or airports. If no match is found among the predefined checks, the route is categorized as “Other”.

However, this categorization approach is not without its limitations. Since it relies on a static SWITCH logic and manual matching of specific airport names within the route strings, it is not feasible to include every possible airport or route covered in the dataset. The result obtained in the graph shows that most reviews are associated with the “Other” category, followed by routes within Europe. This can be easily understood considering the limitation explained.

Exploiting the new calculated column “Route_Category”, in figure 5.3.3 is shown a scatterplot titled "Average of Overall Rating by Route Category" that delves into the relationship between route and overall ratings. The graph is obtained by inserting the newly calculated value “Route_Category” in the x-axis while on the y-axis is evaluated the Average of the variable “Overall Rating” for each route.

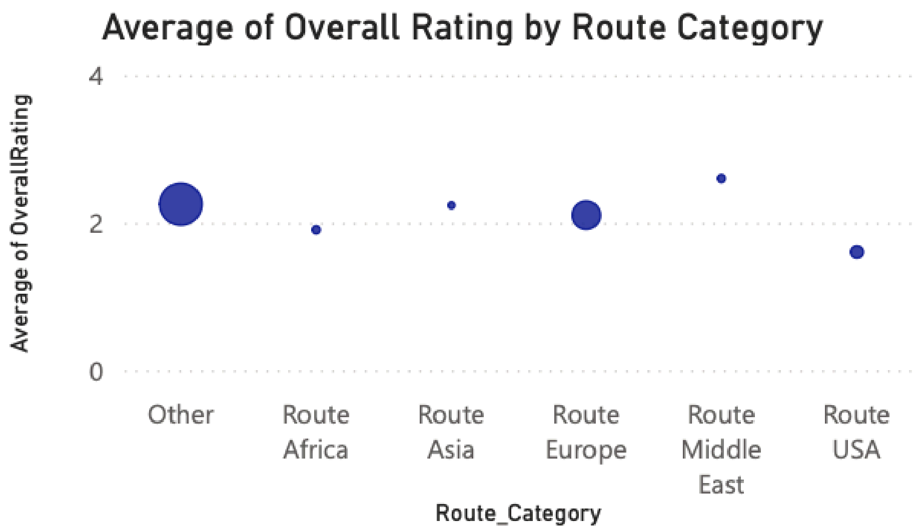

Figure 5.3.3 - Average of Overall Rating by Route Category

Despite their relatively small sample sizes, some routes (such as the Middle East) appear to receive higher average ratings, while more common ones like “Other” or “Europe” tend to hover around lower satisfaction levels.

In figure 5.3.4 is shown a bar chart titled “Number of reviews by Aircraft”, which highlights the aircraft categories that have been most frequently reviewed. The chart is obtained by inserting on the x-axis the count of reviews, while on the y-axis the aircraft category, again a classification obtained through a DAX formula that will be now explained.

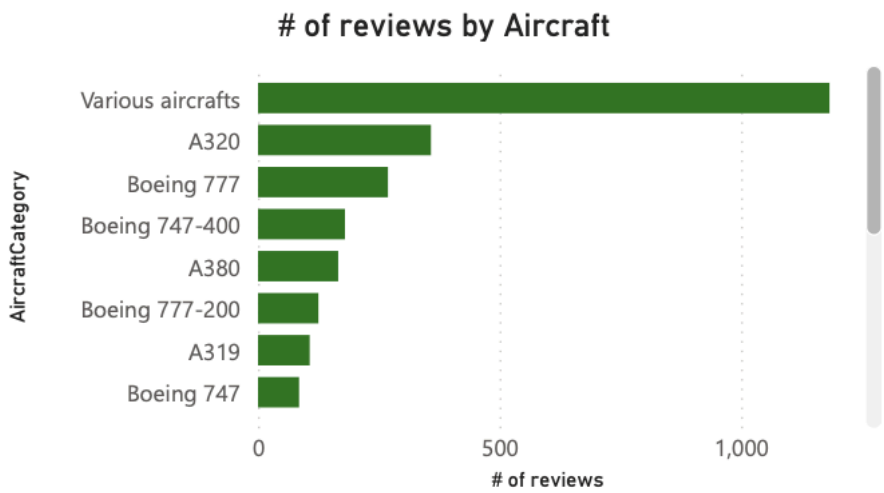

Figure 5.3.4 - Number of reviews by Aircraft

As for the "Route Category" field, the new calculated column "Aircraft Category" has been obtained evaluating the column "Aircraft" row by row across the dataset through a DAX formula. This has been fundamental to improve the analytical quality and consistency of the dataset. The original "Aircraft" column was non-normalized, because it contained a wide variety of values, many of which were sparse or inconsistently reported. In particular, a significant number of reviews referenced aircraft types that appeared only a few times throughout the dataset, making it difficult to derive meaningful insights from such limited data points.

The implemented DAX formula shown in code 5.3.2 addresses this issue by evaluating the number of reviews associated with each unique aircraft model. If a specific aircraft type appears in 10 or fewer reviews, or if the aircraft field is marked as "N/A", the record is grouped under a generalized label: "Various aircrafts". Otherwise, the original aircraft type is retained as its own category.

The threshold of 10 reviews was selected arbitrarily but based on empirical observation: a pivot table analysis in Excel showed that, on average, each aircraft in the dataset was reviewed approximately 14 times, with numerous aircrafts with only one review. This cutoff allowed for a balance between preserving detail and reducing noise caused by outliers or underrepresented entries.

Another significant challenge with this column was the high frequency of missing values, because many reviews simply did not specify the aircraft used. This is likely due to the fact that such information is not always transparent or accessible to passengers. The formula thus serves the dual purpose of normalizing the data and mitigating the impact of incomplete entries, enabling a more effective and focused analysis.

```
AircraftCategory =
VAR AircraftReviewCount =
   CALCULATE(
       COUNTROWS(BA_AirlineReviews),
       ALLEXCEPT(BA_AirlineReviews, BA_AirlineReviews[Aircraft])
   )
RETURN
   IF(AircraftReviewCount <= 10 || BA_AirlineReviews[Aircraft] = "N/A",
       "Various aircrafts",
       BA_AirlineReviews[Aircraft]
   )
```

Code 5.3.2 - AircraftCategory column

The formula begins by defining a variable named AircraftReviewCount, which calculates the number of reviews associated with each unique aircraft. This is done through the following functions:

- The CALCULATE function, combined with COUNTROWS counts the total number of rows, which means the number of reviews for each aircraft. The ALLEXCEPT function ensures that the count is grouped by the Aircraft value alone, ignoring any other filters that might be active in the report. This step effectively determines how frequently each aircraft appears in the dataset.
- The RETURN statement evaluates a conditional expression using the IF function. If the number of reviews for a particular aircraft is less than or equal to 10, or if the aircraft information is not available, which means the N/A field, the aircraft is assigned the generic label "Various aircrafts". Otherwise, the formula retains the original aircraft name.

The result shows that the "Various aircrafts" label dominates, followed by the A320 and Boeing 777 families. The A320 family is one of the most common short to medium haul aircraft categories[13], while the Boeing 777 family is one of the most common long haul aircraft categories[14]. These distributions help contextualize the volume of feedback coming from different flight experiences, which is essential for interpreting satisfaction scores in a meaningful way.

Exploiting the new calculated column "Aircraft Category", in figure 5.3.5 is shown a scatter plot titled "Average of Overall Rating by Aircraft Category" which shows the relationship between Aircraft Category e Overall Rating. The graph is obtained by inserting the newly calculated value "Aircraft Category" in the x-axis while on the y-axis is evaluated the Average of the variable "Overall Rating" for each Aircraft.

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[13] Giacomo Amati, *Airbus' Most Popular Aircraft Designs*, Simpleflying, 20th of January 2024, https://simpleflying.com/airbus-most-popular-designs-list/ consulted on the 4th of June 2025.
[14] AeroTime Editorial, *The Biggest Passenger Planes in the World 2025*, AeroTime, 9th of January 2025, https://www.aerotime.aero/articles/top-10-largest-passenger-planes-in-the-world consulted on the 4th of June 2025.

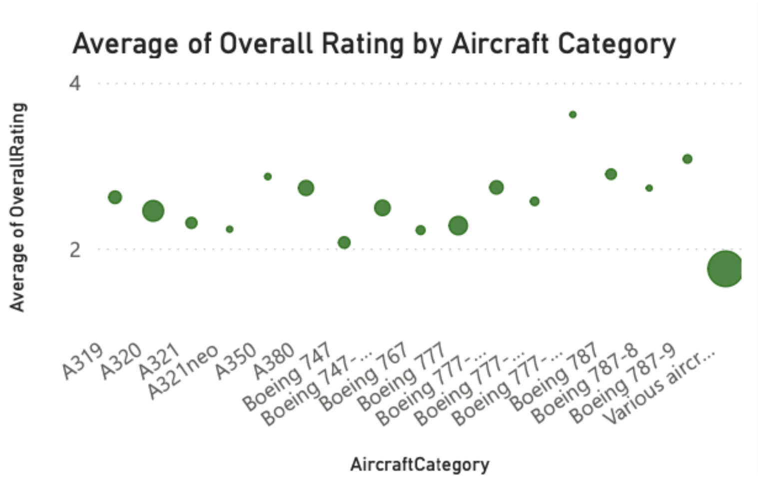

Figure 5.3.5 - Average of Overall Rating by Aircraft Category

Aircraft like the A350 and A380 seem to receive slightly higher ratings, while reviews of "Various aircrafts" tend to yield lower scores. This suggests that the aircraft model does indeed influence the passenger experience, potentially due to differences in onboard amenities, space, or overall comfort.

Finally, in figure 5.3.6 is shown a key influencers card, which identifies the most influential variables that drive an increase in the overall rating. To obtain this result, a key influencer card has been selected from the available visualizations in PowerBI, analyzing the value of Overall Rating explained by the average values of the different parameters evaluated by customers.

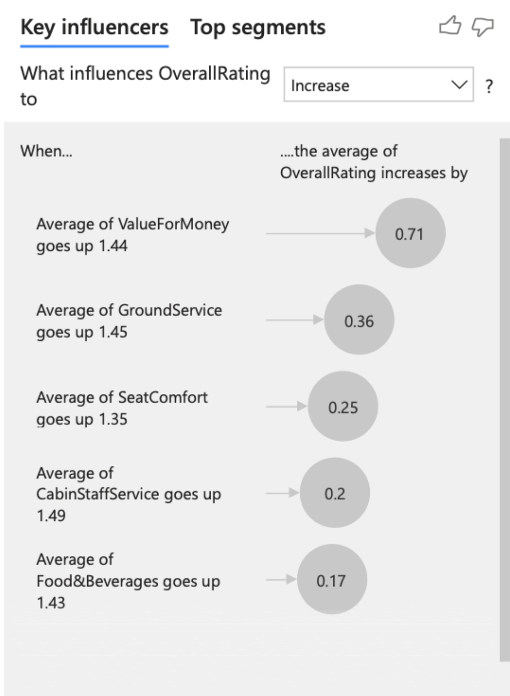

Figure 5.3.6 - Key Influencers of the Overall Rating

According to the visual, “Value for Money” has the most significant positive effect, because when its score increases by 1.44, the average overall rating rises by 0.71 points. Other notable drivers include “Ground Service”, “Seat Comfort”, “Cabin Staff Service”, and “Food and Beverages”, though with progressively smaller impacts. The parameters “Inflight Entertainment” and “Wifi and Connectivity” have no influence on the overall rating. This component of the report is critical for decision-makers, as it quantifies which aspects of the customer experience have the greatest potential to enhance satisfaction if improved.

To conclude, this dashboard page combines trend analysis, categorical comparisons, and driver insights to offer a robust understanding of what affects airline passenger satisfaction. It goes beyond descriptive data, moving into diagnostic insights that can guide strategic improvements in airline services.

5.3.1 Limitations of the manual route classification approach and proposal of scalable methods

As already pointed out in the analysis of the DAX-hard coded formula to categorize route in a more readily usable data, the presented solution may lead to the misclassification of some routes or the overuse of the generic "Other" category, particularly for less frequent or inconsistently formatted entries. Moreover, as the dataset expands or new data is integrated, maintaining and updating this logic manually could become increasingly complex and error-prone.

For these reasons, a more dynamic and scalable method for route classification should be implemented, to allow for greater flexibility, improved accuracy, and better long-term maintainability of the data model.

The primary issue of the method proposed, lies in the fact that the formula only parses a portion of the route string (typically the origin) and compares it to a manually defined list of known airports or cities. This approach, while practical in small-scale, proof-of-concept environments, fails to generalize to datasets with more complex, inconsistent, or non-standardized route formats. To overcome these constraints and make the model more adaptable to future data growth and integration, a scalable, dynamic classification method is recommended.

A possible alternative strategy can be to exploit a geographic clustering based on airport coordinates and IATA airport codes. This method leverages spatial data, specifically, the geographical coordinates (latitude and longitude) of the departure and arrival airports, to group flight routes into meaningful regional categories based on physical proximity. Instead of relying on manually hard-coded airport names or cities, this solution dynamically analyzes the spatial distribution of route endpoints and assigns each route to a regionally coherent cluster.

The process involves the following steps:

1. Extracting the origin and destination from each route string and mapping them to standardized airport codes, such as those provided by the International Air Transport Association (IATA). These codes are then used to retrieve the corresponding geographical coordinates and related metadata from a reference table. This reference table is integrated into the Power BI data model, enabling seamless and efficient mapping between route data and airport-specific information necessary for geographical classification. The table will be updated whenever a new categorization of airports and their corresponding codes is released.
2. Once this spatial data is available, a clustering algorithm such as K-Means or DBSCAN will be applied to identify natural groupings of routes based on geographic distance. K-Means is a centroid-based clustering algorithm that partitions the dataset into a predefined number of clusters by minimizing the variance within each group. It iteratively assigns each data point, in this case, each route's geographic location, to the nearest cluster center, recalculating the centroids until a stable configuration is reached. This method is particularly effective when the number of desired clusters, in this specific case would be five global regions, is known in advance and the spatial distribution is relatively uniform. DBSCAN, Density-Based Spatial Clustering of Applications with Noise, does not require a predefined number of clusters and instead groups data points that are closely packed together, based on a distance threshold and minimum number of neighboring points. It is especially useful for identifying irregularly shaped clusters and can handle noise or outlier routes that do not belong to any major region. This makes DBSCAN more adaptable to complex or uneven geographical distributions, such as overlapping flight zones or sparsely connected regions. In cases where only the origin of the route is considered, clustering is performed directly on the origin points. Alternatively, the geographic centroid of the route, calculated as the midpoint between origin and destination, can be used as the basis for classification, allowing each route to be positioned spatially and classified accordingly.

Although Power BI does not natively support clustering algorithms such as K-Means or DBSCAN, it is still possible to apply them through integration with Python. In practice, this involves enabling Python scripting within Power BI and using it directly in the Power Query environment. Once the airport coordinates and route data have been loaded, a Python script can be executed to perform the clustering using external libraries. The output will consist of the original dataset enriched with an additional column representing the assigned cluster. This new field becomes immediately usable in the Power BI data model, allowing routes to be grouped and visualized by their spatial similarity. This approach combines the analytical power of machine learning with the flexibility of Power BI's visualization tools, making it a scalable and repeatable solution for classifying airline routes in a more accurate and automated way.

The resulting classification enhances the reliability of regional comparisons in customer satisfaction, improves the precision of performance benchmarking, and supports more targeted operational strategies across route networks.

In summary, while the current rule-based classification fulfilled its role for the initial version of the analysis, its limitations in terms of completeness and scalability justify the development of a more automated and metadata-driven method. Such improvements would enable more accurate segmentation of passenger feedback by route, thereby enriching the analytical depth and actionability of the dashboard in operational contexts.

5.3.2 Limitations of the manual aircraft classification approach and proposal of scalable method

While the classification method applied to aircraft data effectively reduced noise and improved the readability of results, it also introduced important limitations. The approach relied on a simple DAX formula that grouped all aircraft types with ten or fewer reviews, as well as those with missing values, under the general label "Various aircrafts." Although this decision was supported by empirical observations, such as the average of 14 reviews per aircraft and the presence of many models with only one entry, it remains a rule-based and static solution.

This threshold-based method lacks scalability and prevents a deeper understanding of aircraft performance when data is sparse. Moreover, it does not account for technical similarities or operational characteristics shared across aircraft families. As a result, potentially meaningful patterns may be lost due to the oversimplification of categories, especially when individual models are analyzed in isolation.

An effective and scalable alternative to the current manual classification of aircraft involves integrating internal operational data from the airline's fleet management system. Most airlines maintain a centralized fleet registry or technical inventory database containing detailed information on each aircraft currently or previously in service. These internal records typically include structured attributes, such as aircraft registration code, model and submodel, aircraft family, cabin configuration, aircraft category, entry into service (EIS) date and flight range classification among short, medium and long haul.
By cross-referencing this internal fleet table with the "Aircraft" field from the review dataset, it becomes possible to build a much more robust classification model. The

mapping key can be the aircraft model name or a standardized variant extracted through Power Query. Once linked, the enriched dataset allows grouping aircraft not only by name, but also by technical family, range category, or age.

This integration provides several advantages over the current rule-based approach:

- It allows automatic categorization even for aircraft with few reviews, as long as they appear in the fleet register;
- It ensures consistency with strategic segmentation;
- It enables dynamic analysis by fleet generation, age, or configuration, allowing insights not just into individual models but into operational classes of aircraft.

In Power BI, the internal fleet table can be loaded into the data model as a dimension table and linked via a one-to-many relationship to the review table. This setup allows the use of hierarchies, such as Model > Family > Range and supports drill-down analysis. Additionally, because this solution leverages internal systems, it provides the foundation for long-term maintainability and seamless updates as the fleet evolves.

Ultimately, incorporating aircraft metadata from native enterprise systems adds strategic depth to the analysis and aligns the dashboard with the airline's operational structure, supporting decisions on fleet performance, renewal strategies, and service standardization across aircraft types.

5.4 Analysis of "Analysis by category" page of the dashboard

This page of the dashboard aims to provide a detailed breakdown of customer review ratings across different route categories and aircraft categories, the new calculated columns whose definition has been explained in paragraph 5.3. The analysis focuses on the average value of the parameters evaluated by customers, with the goal of enabling comparisons not only between different types of routes and aircrafts in terms of perceived service quality, but also considering a fundamental filtering categorization which involves the date, the seat type and the type of traveller.

In figure 5.4.1 is shown a clustered bar chart titled "Average of Categories by Route" which presents the average rating on a scale from 1 to 5 of all the parameters evaluated by the customers, clusterized by the route categories calculated by the DAX formula. The chart is obtained by inserting in the y-axis the route category, while in the x-axis all the parameters considered.

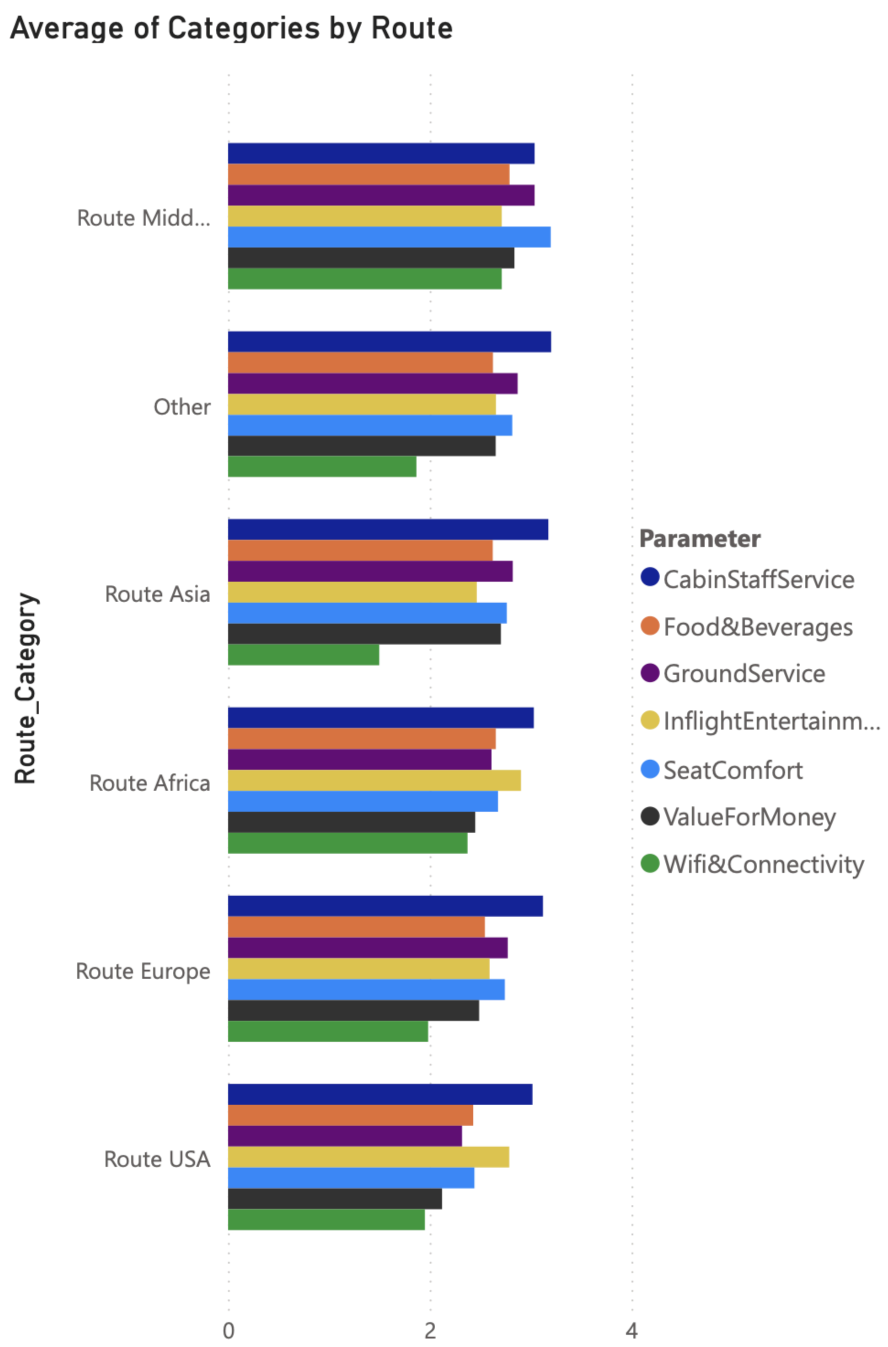

Figure 5.4.1 - Average of Categories by Route

From this chart, it is possible to observe service quality perceptions across different routes. Considering the layout shown in figure 5.4.1, in which no filters have been applied, the route Europe and the route Middle East appear to receive relatively high ratings in all the parameters, except for the Wifi and connectivity parameters in case of European route. The "Other" category shows more variation, likely due to the heterogeneity of the underlying data.

In figure 5.4.2 is shown the same type of clustered bar chart titled “Average of categories by aircraft”, which presents again the average rating on a scale from 1 to 5 of all the parameters evaluated by the customers, clusterized by the new column aircraft categories calculated by the DAX formula as explained in paragraph 5.3. The chart is obtained by inserting in the y-axis the aircraft category, while in the x-axis all the parameters considered.

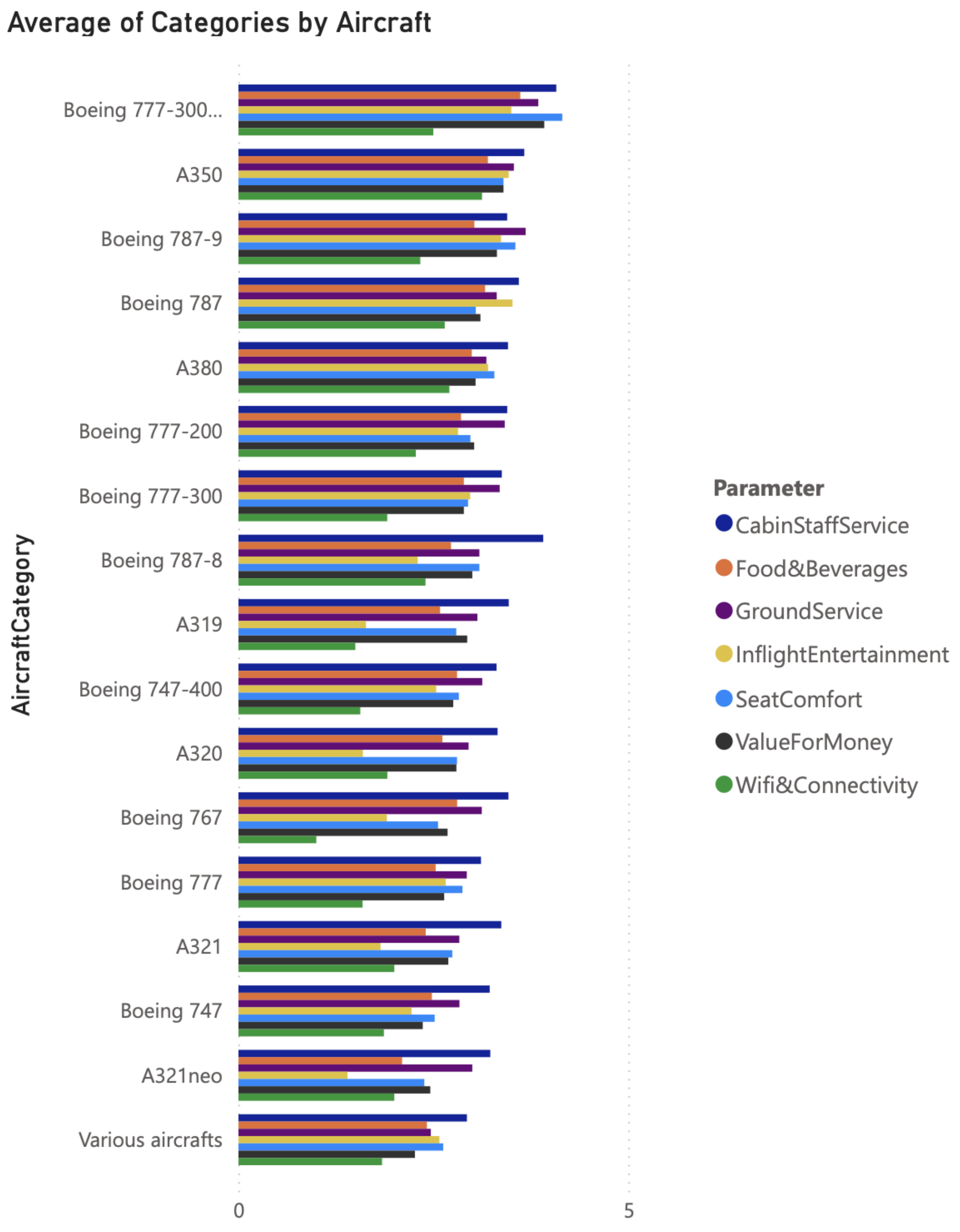

Figure 5.4.2 - Average of Categories by Aircraft

The visualization highlights how different aircraft types are associated with varying levels of customer satisfaction. Considering the layout shown in figure 5.4.2, in which no filters have been applied, it is clearly visible as when considering the parameters cabin staff service and seat comfort, aircrafts from the 777 family have a higher average score with respect to all the other aircrafts. In general it is possible to state that there is a high variability considering both the different types of aircrafts, but also among the various parameters evaluated by customers. In general this comparison can allow stakeholders to identify which aircraft models may be contributing in a more positive or negative way to the perception of the airline.

In chapter 6, discussion of the results, both those graphs will be further analyzed considering also the filtering system implemented to allow the extraction of valuable information.

In figure 5.4.3 is instead shown the filter selection implemented in this page of the dashboard. One of the most powerful and valuable features of Power BI it is in fact its interactive filtering functionality, which plays a crucial role in enabling dynamic, user-driven data exploration. In the context of this project, filters allow for targeted segmentation of the data across multiple dimensions and interactivity transforms a static dashboard into a flexible analytical tool capable of answering specific business questions in real time.

When creating dashboards in Power BI, it is always possible to filter results, but in the specific case of the visualization in this "Analysis by category" page, it has been decided to insert the filtering section directly in the page, because this allows a more dynamic analysis.

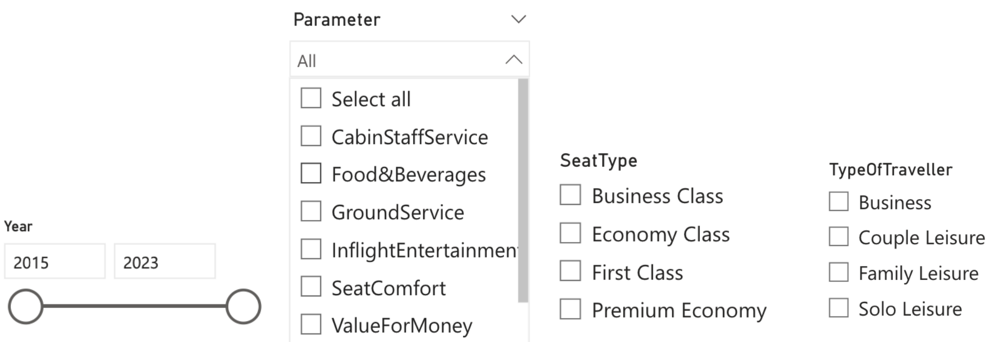

Figure 5.4.3 - Filters selection

Specifically the filter inserted are:

1. Year filter, which allows users to select a range of years from 2015 to 2023, the years in which the data were collected from customers. This is useful for temporal analysis, enabling the examination of how customer satisfaction metrics evolved over time or how specific route or aircraft performance has changed.
2. Parameter filter, which allows users to exclude categories evaluated by customers that are not directly taken into consideration during that specific analysis, allowing focus on the specific parameter discussed.
3. Seat type filter, which includes all the options available in the review form. This is useful to compare service perception across different cabin classes, because in this specific case, clusterization of the perception of the customer to infer service improvement activities is fundamenta.
4. Type of traveller filter, which includes all the options available in the review form. This enables an analysis of whether perceptions differ significantly depending on the passenger profile.

These filters substantially enhance the dashboard's interactivity, allowing users to perform multidimensional analyses and to tailor insights according to specific customer segments or time periods. In particular, the ability to combine multiple filters enables highly targeted evaluations of the results, thereby improving the depth and precision of the analysis.

5.5 Analysis of "Average of parameters" page of the dashboard

In this final page of the dashboard it is explored the temporal evolution of the 7 key passenger experience parameters based on yearly average scores from 2015 to 2023. By observing their trends over time, it is possible to draw meaningful insights into the dynamics of customer satisfaction and identify possible areas of service deterioration or improvement. This page is in fact particularly useful to derive potential corrective actions to perform in case of customer dissatisfactions.

In order to obtain the graph shown in Annex D, it was necessary to create a new table in the Data Model of the project. The new table is made of the now described columns:

1. The column "Year", where the years of observation of the data are inserted;
2. The column "TypeOfTraveller", where the traveller's profile type is inserted for each review;
3. The column "SeatType", where the traveller's seat type is inserted for each review;

4. The column "Route_Category", where the traveller's route categorization previously described is inserted for each review;
5. The column "AircraftCategory", where the traveller's aircraft categorization previously described is inserted for each review;
6. The column "Value" where all the scores for each parameter, year and customer are inserted.
7. The column "Parameter", where all the variables evaluated by customers have been inserted.

This table replicates part of the main dataset of the model, but the new table structure allows the design of the graph in a meaningful way for the analysis.

To create the table the function "New table" has been used, defined through the formula shown in code 5.5.1.

```
TableOfParameters =
VAR BaseTable =
   SELECTCOLUMNS(
       BA_AirlineReviews,
       "Year", YEAR(BA_AirlineReviews[Datetime]),
       "TypeOfTraveller", BA_AirlineReviews[TypeOfTraveller],
       "SeatType", BA_AirlineReviews[SeatType],
       "Route_Category", BA_AirlineReviews[Route_Category],
       "AircraftCategory", BA_AirlineReviews[AircraftCategory],
       "CabinStaffService", BA_AirlineReviews[CabinStaffService],
       "Food&Beverages", BA_AirlineReviews[Food&Beverages],
       "GroundService", BA_AirlineReviews[GroundService],
       "InflightEntertainment", BA_AirlineReviews[InflightEntertainment],
       "SeatComfort", BA_AirlineReviews[SeatComfort],
       "ValueForMoney", BA_AirlineReviews[ValueForMoney],
       "Wifi&Connectivity", BA_AirlineReviews[Wifi&Connectivity]
)
RETURN

   UNION(
       SELECTCOLUMNS(BaseTable, "Year", [Year], "TypeOfTraveller", [TypeOfTraveller], "SeatType",
[SeatType], "Route_Category", [Route_Category], "AircraftCategory", [AircraftCategory], "Parameter",
"CabinStaffService", "Value", [CabinStaffService]),
       SELECTCOLUMNS(BaseTable, "Year", [Year], "TypeOfTraveller", [TypeOfTraveller], "SeatType",
[SeatType], "Route_Category", [Route_Category], "AircraftCategory", [AircraftCategory], "Parameter",
"Food&Beverages", "Value", [Food&Beverages]),
       SELECTCOLUMNS(BaseTable, "Year", [Year], "TypeOfTraveller", [TypeOfTraveller], "SeatType",
[SeatType], "Route_Category", [Route_Category], "AircraftCategory", [AircraftCategory], "Parameter",
"GroundService", "Value", [GroundService]),
       SELECTCOLUMNS(BaseTable, "Year", [Year], "TypeOfTraveller", [TypeOfTraveller], "SeatType",
[SeatType], "Route_Category", [Route_Category], "AircraftCategory", [AircraftCategory], "Parameter",
"InflightEntertainment", "Value", [InflightEntertainment]),
       SELECTCOLUMNS(BaseTable, "Year", [Year], "TypeOfTraveller", [TypeOfTraveller], "SeatType",
[SeatType], "Route_Category", [Route_Category], "AircraftCategory", [AircraftCategory], "Parameter",
"SeatComfort", "Value", [SeatComfort]),
       SELECTCOLUMNS(BaseTable, "Year", [Year], "TypeOfTraveller", [TypeOfTraveller], "SeatType",
[SeatType], "Route_Category", [Route_Category], "AircraftCategory", [AircraftCategory], "Parameter",
"ValueForMoney", "Value", [ValueForMoney]),
       SELECTCOLUMNS(BaseTable, "Year", [Year], "TypeOfTraveller", [TypeOfTraveller], "SeatType",
[SeatType], "Route_Category", [Route_Category], "AircraftCategory", [AircraftCategory], "Parameter",
"Wifi&Connectivity", "Value", [Wifi&Connectivity])
)
```

Code 5.5.1 - Table of parameters

Firstly, this function creates a new temporary variable called “BaseTable” in which all the columns needed to create the new table are selected from the main model. Then the UNION function allows stacking the resulting smaller tables into one unified structure. The smaller tables are obtained thanks to the function SELECTCOLUMNS which takes from the variable “BaseTable” all the correct data for each review, creating the new structured table.

Finally to obtain the graph in Annex D it was created a line chart with the variable year in the x-axis, the average of the variable value in the y-axis and the variable parameter in the legend. Moreover two slicers with the years of observation and the parameters evaluated have been inserted, in order to be able to evaluate the results more dynamically. In the whole page were also inserted the filters aircraft category, route category, seat type and type of traveller to make the page coherent with the others analysis.

Trending lines will now be evaluated parameter by parameter to avoid misunderstanding with all the stacked lines.

In figure 5.5.1 it is shown the line chart which describes the distribution of the average of the parameter value for money through the years of observation.

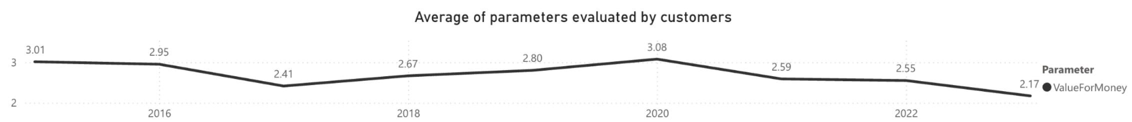

Figure 5.5.1 - Average of value for money through years

After remaining relatively stable in 2015 and 2016, its average rating experienced a sharp decline in 2017. This drop coincided with the overall decrease in satisfaction observed in figure 5.3.1. From 2018 onwards, there was a progressive recovery, culminating in peak values between 2020 and 2021. However, this improvement was not sustained in the most recent years, with scores once again declining in 2022 and 2023, highlighting ongoing volatility in passengers’ perception of this variable.

In figure 5.5.2 it is shown the line chart which describes the distribution of the average of the parameter Wi-Fi and connectivity through the years of observation.

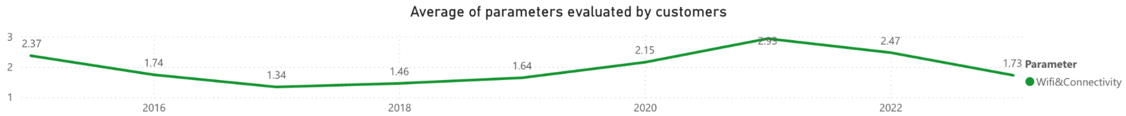

Figure 5.5.2 - Average of Wi-Fi & Connectivity through years

Wi-Fi connectivity exhibits a distinct trend compared to other service categories. Following a period characterized by stagnation and generally low satisfaction levels, a marked improvement was observed between 2020 and 2021. This positive shift may be attributed to digital transformation initiatives and infrastructure upgrades implemented during or in the aftermath of the COVID-19 pandemic. However, the subsequent slight decline recorded in 2022 and 2023 could indicate an uneven adoption of such improvements across airlines, or alternatively, a rise in passenger expectations that have not been consistently met.

In figure 5.5.3 it is shown the line chart which describes the distribution of the average of the parameter seat comfort through the years of observation.

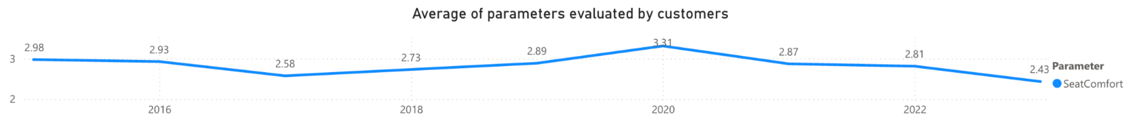

Figure 5.5.3 - Average of seat comfort through years

The seat comfort parameter experienced a stable period until 2016, but like most of the other variables, registered a significant decline in 2017. A gradual improvement can be seen between 2018 and 2020, followed by another decrease in the last two years of observation.

In figure 5.5.4 it is shown the line chart which describes the distribution of the average of the parameter inflight entertainment through the years of observation.

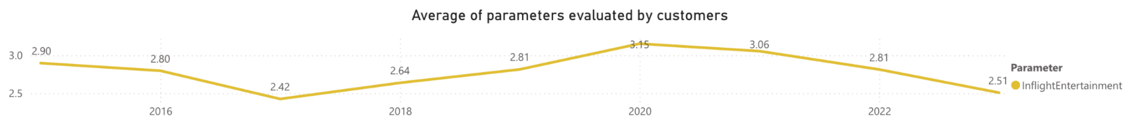

Figure 5.5.4 - Average of inflight entertainment through years

The inflight entertainment parameter followed a similar trajectory, with declining scores around 2017, followed by an upward trend until 2021 and again a slight decrease from 2021 to 2023.

In figure 5.5.5 it is shown the line chart which describes the distribution of the average of the parameter ground service through the years of observation.

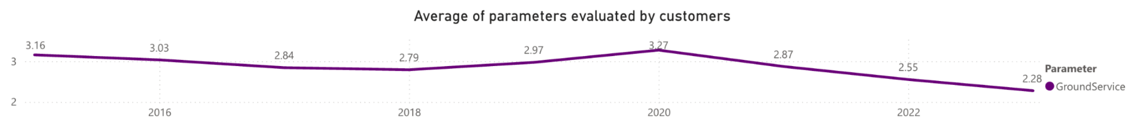

Figure 5.5.5 - Average of ground service through years

Ground service presents the same pattern of the other parameters, but with a lower deviation from the average value up to 2020.

In figure 5.5.6 it is shown the line chart which describes the distribution of the average of the parameter food and beverages through the years of observation.

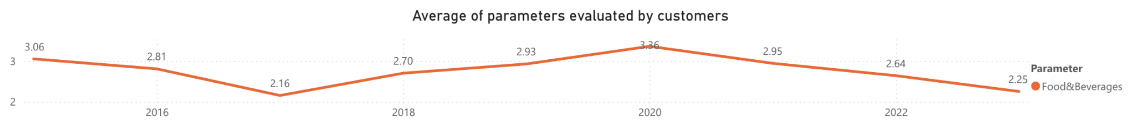

Figure 5.5.6 - Average of food and beverages through years

Food and beverages also followed the already described pattern, with a significant drop in 2017, followed by gradual improvements that peaked around 2020–2021 and declined again afterward.

In figure 5.5.7 it is shown the line chart which describes the distribution of the average of the parameter cabin staff service through the years of observation.

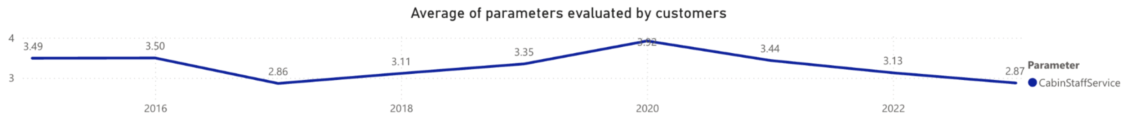

Figure 5.5.7 - Average of Cabin staff service through years

The cabin staff service parameter followed the same trajectory seen in the other variables, with declining scores around 2017, followed by an upward trend until 2020 and again decreasing trend from 2021 to 2023.

This section of the dashboard, along with the three previously analyzed, functions as a comprehensive visualization tool for exploring the correlation between passenger satisfaction ratings, route characteristics, and aircraft types. The insights derived from these dashboards provide valuable support for data-driven decision-making in key operational areas such as fleet management, service enhancement, and route optimization, topics that will be examined in greater detail in the following chapter.

6. Discussion of the results

The objective of this chapter is to analyze and interpret the results derived from the Power BI dashboards developed in the context of this thesis project. The primary focus is to examine how customer reviews reflect the airline's performance across various service dimensions, routes, aircraft types, and over time. By leveraging the structured visualizations and aggregations of user-generated feedback, the analysis aims to extract meaningful insights that highlight both operational strengths and potential areas for improvement.

The analysis is structured around three key areas. First, attention is given to the temporal evolution of the results, with the objective of identifying potential trends that could inform future projections, as well as gaining insight into how customer perceptions of service may have been influenced by external factors during different time periods.
Second, the analysis explores how passenger experiences vary according to the geographical routes of the flights, highlighting regional differences in satisfaction levels.
Finally, patterns in customer satisfaction are examined in relation to the type of aircraft operated, with a particular focus on aircraft-specific characteristics that may impact comfort and perceived service quality.

This chapter plays a central role in this study, because in a highly competitive and service-driven industry like aviation, understanding passenger perceptions is crucial for enhancing service delivery, optimizing resource allocation, and improving brand reputation. The insights derived from this approach can inform and guide decision-making ultimately contributing to a more customer-centric airline experience.

6.1 Temporal trends

The first input on the analysis of temporal trends is given by the graph shown in figure 5.3.1, which shows the trend of overall rating through the years. The graph highlights two concerning situations, the first one in 2017 with a drop of the average value of overall rating from 2016 of around 24% and the second one in 2020, with a steadily drop of the average value of overall rating from 2020 to 2023 with annual declines of 8.5%, 12.4%, and 23.4%, respectively, indicating an accelerating downward trajectory.

Those two episodes will now be analyzed in more detail, trying to understand which are the key influencers to these conditions, if the two decreases are by any chance correlated and deriving possible corrective actions that the airline can perform to improve the score.

6.1.1 Analysis of 2017 drop in overall rating

In order to analyze this trend, the first action taken is to evaluate key influencers indicator card available in the "Overall Rating" dashboard in Annex B, comparing the parameters that influenced overall rating in 2016 and in 2017.

In figure 6.1.1.1 is shown the result of the key influencers card in 2016, while in figure 6.1.1.2 is shown the result for 2017. In order to make the comparison simpler, the values have been inserted in table 6.1.1.1.

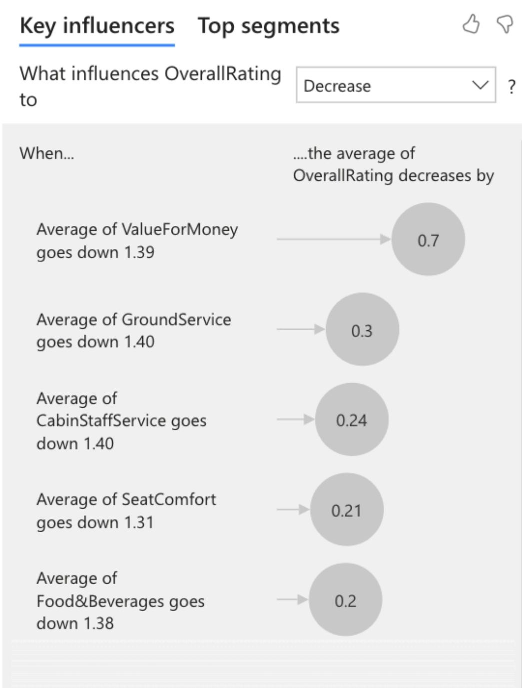

Figure 6.1.1.1 - Key influencers card 2016

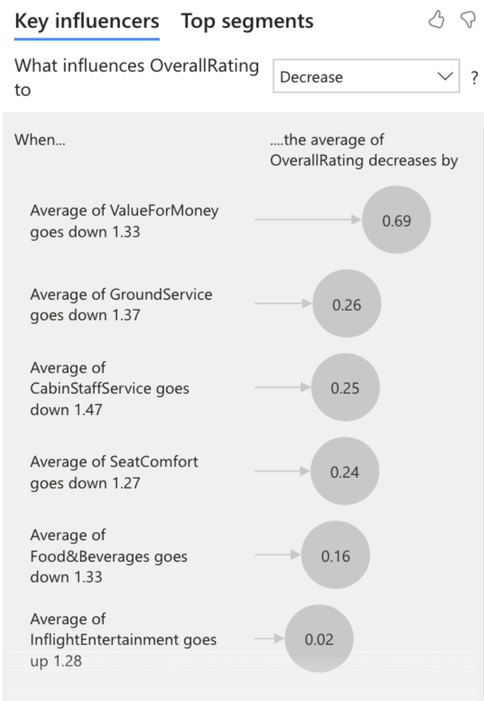

Figure 6.1.1.2 - Key influencers card 2017

	Decrease in 2016	**Decrease in 2017**	**Decrease in Overall Rating in 2016**	**Decrease in Overall Rating in 2017**
Value for money	-1,39	-1,33	-0,70	-0,69
Ground service	-1,40	-1,37	-0,30	-0,26
Cabin staff service	-1,40	-1,47	-0,24	-0,25
Seat comfort	-1,31	-1,27	-0,21	-0,24
Food and Beverages	-1,38	-1,33	-0,20	-0,16
Inflight Entertainment	N/A	+1,28	N/A	-0,02

Table 6.1.1.1 - Key influencers and their impact on Overall Rating 2016-2017

The purpose is to determine whether the variables shown provide a satisfactory explanation for the observed 24% drop in the Overall Rating in 2017.

Across both years, the most influential factor is consistently value for money, with a decrease of -1.39 points in 2016 leading to a -0.70 drop in overall rating, and a slightly lower decrease of -1.33 in 2017 corresponding to a very similar impact of -0.69. This

suggests that passengers' perception of the value received for the price paid plays a central role in shaping their overall satisfaction.
Ground service, cabin staff service, and seat comfort show relatively stable patterns between the two years. Ground service decreased by -1.40 in 2016 and -1.37 in 2017, leading to overall rating drops of -0.30 and -0.26, respectively. Similarly, cabin staff service shows a slightly larger decrease in 2017, -1.47 compared to -1.40, yet its impact on overall rating remains relatively modest and stable with -0.25 compared to -0.24. Seat comfort also exhibits minimal variation in both the decline in score and its contribution to overall rating.
Food and beverages showed a decrease of -1.38 in 2016 and -1.33 in 2017, leading to corresponding overall rating impacts of -0.20 and -0.16, indicating a limited but consistent influence on customer satisfaction, proportional from 2016 to 2017.
An interesting observation concerns inflight entertainment, which in 2016 does not appear as a relevant factor (N/A), while in 2017 it actually shows a positive increase in its average score +1.28, yet its influence on overall rating remains negligible with -0.02. This suggests that improvements in this area were not sufficient to offset declines in more critical dimensions of the service.

When aggregating the effects of all individual contributors, the result obtained is that in 2016 the average impact is -0.33, while in 2017 is -0.27. Surprisingly, the average negative impact on overall rating was higher in 2016 of 0.06 points more than in the following year. This suggests that the observed deterioration in overall rating during 2017 cannot be fully explained by the decline of individual parameters alone. Other latent variables or contextual factors, such as strategic decisions taken by the airline company or competitive changes in the market, not captured in the current set of features might have contributed to the more substantial decline observed in that year. In conclusion, while the individual parameters do show some explanatory power, especially value for money, none of the measured variables alone nor in combination appear to fully explain the severity of the decrease in overall rating recorded in 2017. This reinforces the idea that overall customer satisfaction may depend on a broader ecosystem of service quality, expectations, and market context beyond the measurable performance categories.

In a real life situation, the next step would be to try to segment the client base and understand which is the portion of the customer more affected by this decrease in overall rating. In order to do so, it has been exploited the page “General data” available in Annex A, which allows a more clear categorization of the customer in 2017.

In figure 6.1.1.3 it is shown the graph “Number of reviews by seat type” filtered in the year 2017, which gives a picture of the number of reviews by seat type. The graph shows clearly an unbalancing in the direction of business and economy class travellers reviews. Specifically, of the whole number of reviews for 2017 which is equal to 559 total reviews, 164 correspond to business class and 327 to economy class, respectively around 29% and 58% of the total.

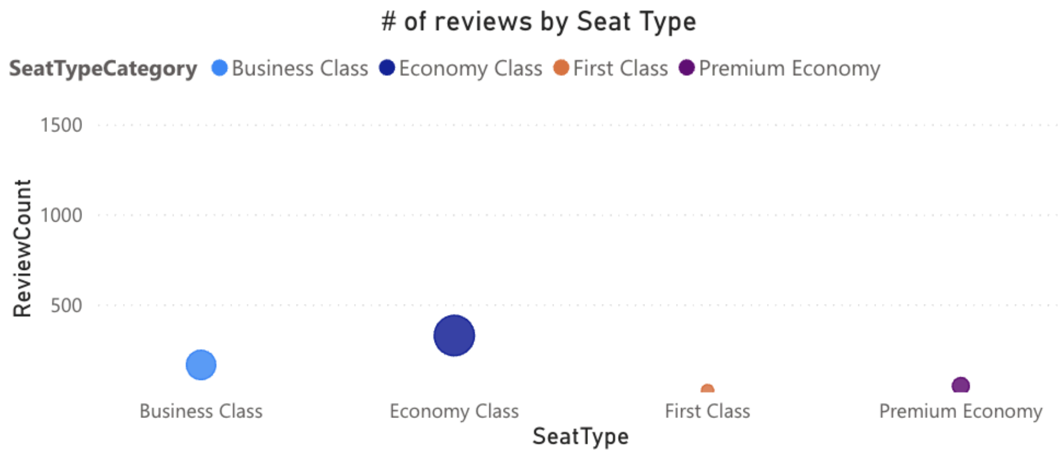

Figure 6.1.1.3 - # of reviews by Seat Type in 2017

Going more in depth it is useful to observe the overall rating in 2016 and 2017 for the two classes of passengers. The result is visible in table 6.1.1.2.

	Overall rating 2016	**Overall rating 2017**
Business class	2.62	2.13
Economy class	2.38	1.69

Table 6.1.1.2 - Overall rating in 2016 and 2017 for Business and Economy classes

It is evident that the Economy class was the most significant contributor to the decline in the overall rating observed in 2017. Compared to 2016, this class experienced a substantial drop of approximately 29%, making it the primary driver behind the overall negative trend.

Once all these considerations have been done, it is easier to cluster the analysis to try to understand the factors that influenced the drop in overall rating in 2017. In order to obtain useful insights on the parameters that can be more involved in this result, the graphs available in Annex D will be exploited. Filtering data in the graphs for the seat type economy class and the two-year period 2016-2017, the result obtained is clear of all the parameters involved with a declining rate.
In order to make the analysis easier, the results have been inserted in table 6.1.1.3.

	Avg in 2016	Avg in 2017	% decrease
Value for money	2.89	2.19	24,22%
Ground service	2.88	2.72	5.56%
Cabin staff service	3.28	2.54	22.56%
Seat comfort	2.86	2.47	13.64%
Food and Beverages	2.56	1.80	29.69%
Inflight Entertainment	2.54	1.26	50.39%
Wifi & Connectivity	1.69	1.27	24.85%

Table 6.1.1.3 - Average of parameters in 2016 and 2017 with % decrease

The comparative analysis between the average scores in 2016 and 2017 has revealed a clear decline across all service parameters evaluated by passengers. However, certain categories experienced more pronounced reductions and are therefore likely to have had a greater influence on the overall decrease in customer satisfaction, even though there was no clear correlation. The most significant declines were observed in inflight entertainment, with a reduction of 50.39%, food and beverages with a reduction of 29.69%, cabin staff service with a reduction of 22.56%, and value for money with a reduction of 24.22%. These areas should be considered strategic priorities in any customer satisfaction recovery plan, taking into consideration also the range of action of the airline in improving those parameters.

The most substantial decline was seen in the inflight entertainment category, which experienced a dramatic drop of over 50.39%. This may suggest that customers perceived a significant degradation in the quality, availability, or usability of the entertainment systems offered during flights. However, for this specific parameter it could be considered also the technological landscape of the period, in fact the timeline aligns with a period in which the airline industry witnessed a shift in passenger expectations, driven by the growing ubiquity of personal streaming services and mobile devices. To address this issue, the airline can consider both short and long term actions. In the short term, the solution may be expanding the content library with more diverse and regularly updated media, and ensuring functionality across all aircraft. Yet, in the long term, some hardware upgrades must be considered, such as modernizing seat-back screens and improving system reliability and implementing streaming services accessible via mobile devices, thereby bridging the expectation gap. Ensuring compatibility and ease of access will be essential to restoring customer satisfaction in this increasingly critical area of service, which will become more important also for economy classes.

The food and beverages category also suffered a sharp decline of 29.69%. This decrease could be linked to reduced menu variety, lower food quality, or cost-cutting measures perceived negatively by passengers. To reverse this trend, the airline should reevaluate its onboard catering policies. Implementing quality control procedures, partnering with reputable catering providers, and offering regionally inspired or customizable meal options may significantly improve customer perception. In particular, considering the statistical increase in the number of passengers with allergies and different dietary habits, taking into account the variety of passenger needs becomes crucial to provide service in line with expectations. Further, conducting regular passenger feedback surveys specific to onboard meals can help tailor offerings more closely to evolving customer expectations.

Wi-Fi and connectivity also experienced a notable decline, with a reduction of approximately 24.85%. Although this category started from a relatively low average rating in 2016, the further drop the following year indicates growing dissatisfaction among passengers or, as for the specific case of inflight entertainment, a mismatch with the technological landscape of the period. Between 2016 and 2017, mobile connectivity and internet access became increasingly critical for travelers, not only for leisure but also for productivity during flights, especially for business travellers. Many passengers began expecting reliable, fast, and preferably free WiFi services, especially on medium to long-haul routes. If the airline's offerings in this area were either absent, inconsistent, or perceived as too costly or slow, this could have strongly influenced negative evaluations. Corrective actions should therefore include investments in more robust in-flight connectivity infrastructure, potentially through partnerships with leading satellite internet providers, but again this is probably a more valuable insight when considering the long-term effects of the actions taken by the airline. Additionally, offering tiered internet packages could address diverse passenger needs without overextending operational budgets. Communicating these improvements clearly before and during the flight would also help manage expectations and improve perceived service quality.

The parameter Value for Money, which declined by 24,22%, reflects an overall customer sentiment that the price paid does not match the perceived quality of service, also because it is the parameter that most influenced the overall rating. To improve this perception, the airline should consider introducing fare transparency initiatives, clearly communicating what is included in each fare type. Furthermore, value-added services such as priority boarding, baggage allowances, or complimentary upgrades for frequent flyers could help justify pricing and enhance perceived value. These potential actions match with what has been done by airlines lately, with the introduction of frequent flyers programs and fidelity programs.

Lastly, a reduction of over 22% in cabin staff service parameters indicates a deterioration in the perception of interpersonal interactions between staff and passengers. Training programs aimed at enhancing soft skills such as empathy, problem-solving, and responsiveness could prove effective. Additionally, incentivizing excellent service performance with economical bonuses and reinforcing a customer-centric culture throughout the cabin crew team may contribute to restoring higher ratings in this category.

Addressing all these critical areas through targeted and data informed interventions can not only reverse the downward trend observed in 2017 but also support long-term customer satisfaction and loyalty. As part of a broader strategic initiative, these corrective actions should be monitored through continuous feedback mechanisms and embedded into the airline's service quality management framework.

6.1.2 Analysis of 2020 to 2023 drop in overall rating

The downward trend in the overall rating observed between 2020 and 2023 cannot be fully understood without placing it within the broader context of the global COVID-19 pandemic and its impact on the aviation industry. Beginning in early 2020, the outbreak of COVID-19 led to an unprecedented disruption of air travel worldwide. Governments imposed strict travel restrictions, lockdowns, and quarantine measures that significantly reduced both domestic and international flight operations. According to IATA data[15], global air traffic in 2020 dropped by over 65.9% year over year from 2019, marking the sharpest decline in the history of commercial aviation.

This sharp contraction in the number of flights and passengers had a direct effect not only on airlines' revenues, but also on their ability to maintain pre-pandemic service standards. Staff shortages, cost-cutting initiatives, and operational constraints became widespread, affecting all aspects of the passenger experience. In many cases, the industry was forced to prioritize operational continuity over service excellence, leading to deteriorations in passenger perception and satisfaction.

From a psychological standpoint, passenger expectations also shifted during this period. Hygiene, safety protocols, and flexibility in ticket policies gained importance, while traditional quality indicators such as catering, comfort, or entertainment took a secondary role. However, as the world gradually reopened and demand for air travel began to recover from 2021 onward, passengers expected a rapid return to pre-pandemic service levels. When such expectations were not met the resulting frustration was often reflected in lower customer ratings, as in this specific case.

The decline in overall rating from 2020 to 2023 thus emerges as a consequence of both structural limitations within the airline industry and the evolving expectations of a

[15] Dawit Habtemariam, *IATA: 2020 Was Worst Year Ever for Aviation Demand, and 2021 Off to a Bad Start,* businesstravelsnews, 4th of February 2021, https://www.businesstravelnews.com/Global/IATA-2020-Was-Worst-Year-in-Aviation-Demand-History-and-2021-Off-to-a-Bad-Start?, consulted on the 14th of June 2025.

post-pandemic customer base. Airlines were required to adapt to changing health regulations and reduced workforce availability, while also facing increasing demands for digital services, seamless communication, and more personalized assistance.
In light of this, it becomes clear that the post 2020 decline in ratings is not solely attributable to performance deterioration, but rather to a complex interplay between external constraints and rising customer expectations in a transformed travel landscape. Understanding this context is essential before proposing any corrective actions or when trying to address the origin of this decrease in overall rating.

That said, in order to understand more about this drop in overall rating through the years 2020 to 2023, it is useful to start analyzing the distribution of reviews among types of travellers, thanks to the graphs available in Annex A.

The total number of reviews in the 3 years is equal to 579 reviews, only 20.1% of the total number or reviews available in the dataset. This is in line with the decrease already explained in the number of travellers during those years, but this also gives a hint about the fact that the results obtained in this specific analysis reflect a particular condition. In figure 6.1.2.1 it is shown the number of reviews considering different types of travellers and seat type.

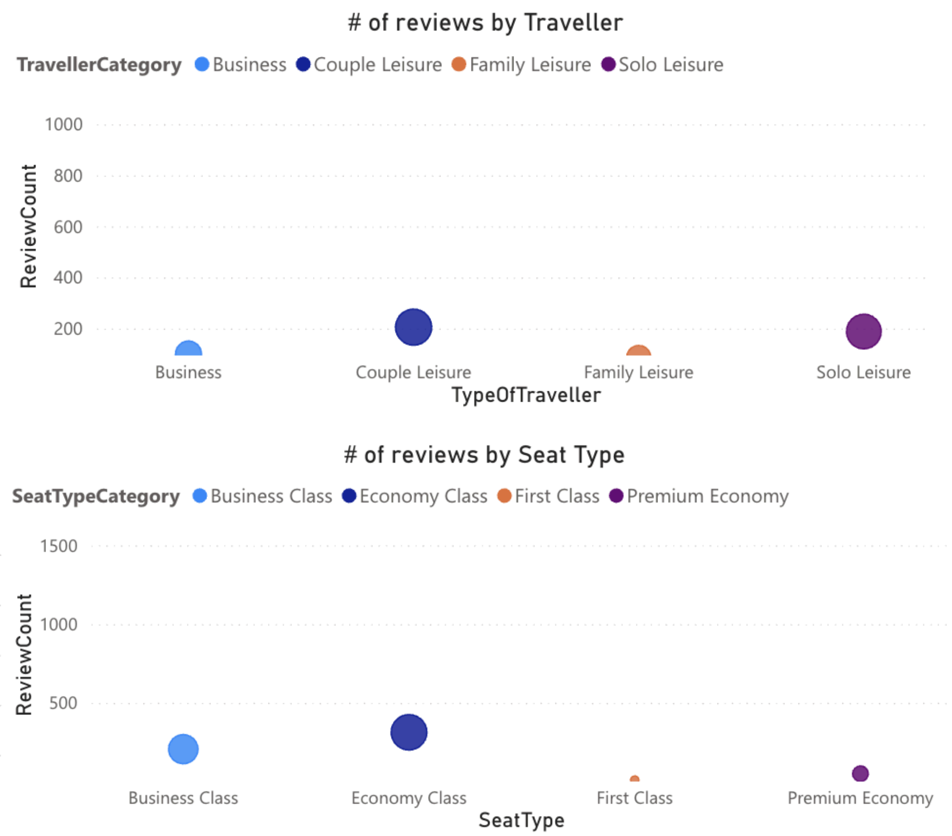

Figure 6.1.2.1 - # of reviews by traveller and seat type in the 3 years from 2020 to 2023

When considering type of travellers, the two categories more involved are couples and solo travellers, specifically 205 couples travellers which corresponds to 35,4% of the total and 188 solo travellers which corresponds to 32,5% of the total.

Instead, when considering seat types, the two categories more involved are business and economy class travellers respectively to 206 business travellers which correspond to 35,6% of the total and 313 economy travellers which correspond to 54.1% of the total.

These distributions are coherent with the expectations, business travellers are less due to the increase of smart working in companies and the declining number of business trips. Group travel, and family vacations were also experiencing major declines.
In contrast, solo and couple travellers, often traveling for personal or essential reasons, were likely among the first to resume air travel, particularly for short or domestic routes. This could explain their dominance in the dataset during this time window.

From the perspective of seat class, the high volume of economy class feedback is particularly significant, as it suggests that a large portion of the declining customer satisfaction may be rooted in the experiences of cost-conscious travellers. During the pandemic and subsequent years, airlines faced financial constraints that often translated into service cutbacks, especially in Economy class. Reduced food and beverage offerings, limited inflight entertainment, and diminished staff-to-passenger ratios are among the issues that may have disproportionately affected economy passengers.

Once the distribution of type of travellers has been clarified, the dashboard in Annex D with the average value for each parameter will be analyzed, considering only the categories more involved.

	Avg in 2020	Avg in 2021	Avg in 2022	Avg in 2023	% decrease from 2020 to 2023
Value for money	3.08	2.59	2.55	2.17	29.55%
Ground service	3.27	2.87	2.55	2.28	30.27%
Cabin staff service	3.92	3.44	3.13	2.87	26.78%
Seat comfort	3.31	2.87	2.81	2.43	26.59%
Food and Beverages	3.36	2.95	2.64	2.25	33.04%
Inflight Entertainment	3.15	3.06	2.81	2.51	20.32%
Wifi & Connectivity	2.15	2.93	2.47	1.73	19.53%

Table 6.1.2.1 - Average of parameters from 2020 to 2023 considering the identified categories

In general, the trend is decreasing through the 3 years for all the parameters except for Wi-Fi and connectivity. Given the considerations already made for the special condition related to the presence of COVID-19, the focus of this analysis will be only on the trends of the parameters of cabin staff service, seat comfort and food and beverages.

The average score for cabin staff service declined from 2020 to 2023 of a total of 26.59%. This parameter encompasses various aspects such as the professionalism, responsiveness, courtesy, and overall attentiveness of the cabin crew, reflecting the quality of human interaction onboard. Due to strict health and safety protocols, many interactions between crew and passengers were limited or highly regulated, prioritizing physical distance over personalized service. The overall onboard environment became more transactional and less focused on hospitality, which likely contributed to the perceived decline in service quality, especially when considering that among all those parameters, cabin staff is the one with the higher score in 2020.
To restore and enhance cabin staff service ratings, it must be taken into account firstly that most of the restrictions related to sanitary aspects will be probably reduced through the years, improving in general the interaction between passengers and cabin crew. Cabin crew were often instructed to minimize contact, limit movement through the cabin, and wait for passengers to make explicit requests rather than initiating service themselves. In many cases, this reduced the opportunity for personal attention and weakened the sense of care that passengers previously associated with premium service. In the post COVID-19 context, the most important thing will be to explain to passengers

the changes in procedures, making clear that everything is done to ensure a safe and smooth travel.

Similarly, seat comfort experienced a decline from 2020 to 2023 of a total of 26.59%. In the pre COVID-19 era, seat comfort was already a critical component of customer satisfaction, especially for medium and long haul flights. Passengers typically evaluated it based on legroom, seat width, cushioning quality, and ergonomic support. In the post COVID-19 era, the low number of activities performed to improve seat comfort during those years and the increased perception of the narrowness of the seat size and the little space available between passengers at a time when the perceived importance of social distance was greatly increased, probably affected negatively the overall score of this parameter. While seat comfort remains a critical parameter in shaping the overall passenger experience, implementing structural changes to improve this aspect presents significant challenges. Modifying seat layout, such as increasing pitch, widening seats, or altering cabin configuration, would require substantial aircraft reengineering. These modifications involve high costs, regulatory approvals, and downtime for the fleet, making them largely unfeasible in the short term. However, passenger perception of comfort is not determined solely by seat dimensions. In the post COVID-19 context, cleanliness, hygiene, and visual cues of safety have become equally important contributors. Introducing disposable seat covers, refreshing upholstery materials more frequently, or implementing visible and thorough cleaning procedures between flights can significantly influence how comfortable and safe passengers feel in their seats. These measures are more operational than structural, and therefore easier and more cost-effective to implement. By reinforcing the perception of a clean and well-maintained seating environment, airlines can address passengers' heightened health sensitivities, thus improving the overall comfort experience without altering the aircraft configuration.

Finally, the parameter food and beverages experienced a decline from 2020 to 2023 of a total of 33.04%. The marked drop is reflective of many cases in which airlines either eliminated meal services entirely on short and medium haul flights or adopted pre-packaged solutions that lacked variety, freshness, and appeal. These changes, while necessary from an operational standpoint, inevitably compromised the perceived quality of the onboard experience. As air travel normalizes through the years, passenger expectations have evolved, particularly with regard to hygiene standards. Therefore, any improvement strategy must prioritize food safety, cleanliness, and transparency in handling and preparation processes. Clearly communicating these practices to passengers can help restore trust in the in-flight dining experience.
However, as highlighted in the 2016–2017 analysis, improving food and beverages ratings cannot rely solely on hygienic measures. It is equally important to focus on the quality, variety, and inclusiveness of the offerings. Airlines should aim to diversify menus by incorporating healthier options, and meals tailored to specific dietary

requirements. Ensuring availability and ease of meal selection during booking or check-in could also enhance the experience. In an increasingly globalized and health-conscious market, personalizing the in-flight culinary experience to meet diverse and evolving passenger preferences will be essential to restoring satisfaction levels in this category.

In conclusion, while the observed decline across these key service areas was likely inevitable given the extraordinary global circumstances, it is essential that airlines now pivot towards strategic reinvestment in the onboard experience, leveraging customer feedback to prioritize initiatives with the greatest impact on perceived quality. Rebuilding trust and satisfaction in these areas will be crucial to restoring overall customer sentiment and, consequently, the overall rating.

6.2 Route based analysis

Temporal trends are extremely useful to understand customer behaviors over time and also how economical and geopolitical circumstances can influence perception of the service offered by airlines. However, in a real-life situation, a more specific categorization can help understand easily and more efficiently which are the characteristics of the service on which intervention is needed to improve travellers' experience.

Analyzing average ratings by route category allows for a more targeted understanding of where service weaknesses and strengths are most prominent. For this analysis, only five out of six route categories were considered: Asia, Europe, Middle East, Africa, and the United States, excluding the "Other Routes" category due to its lack of clear geographical definition and practical actionability. This brings the total number of reviews used as sample for this analysis to 944 reviews, which are distributed among the different routes as in table 6.2.1.

	Route Africa	**Route Asia**	**Route Europe**	**Route Middle East**	**Route USA**
Tot # of reviews	31	17	765	25	106
% of the total # of reviews	3.28%	1.80%	81.03%	2.65%	11.23%

Table 6.2.1 - Distribution of reviews per route

In figure 6.2.1 it is shown the graph "Average of categories by route", excluding the category other route, where the average of all the parameters is shown at the end of each bar representing the category evaluated.

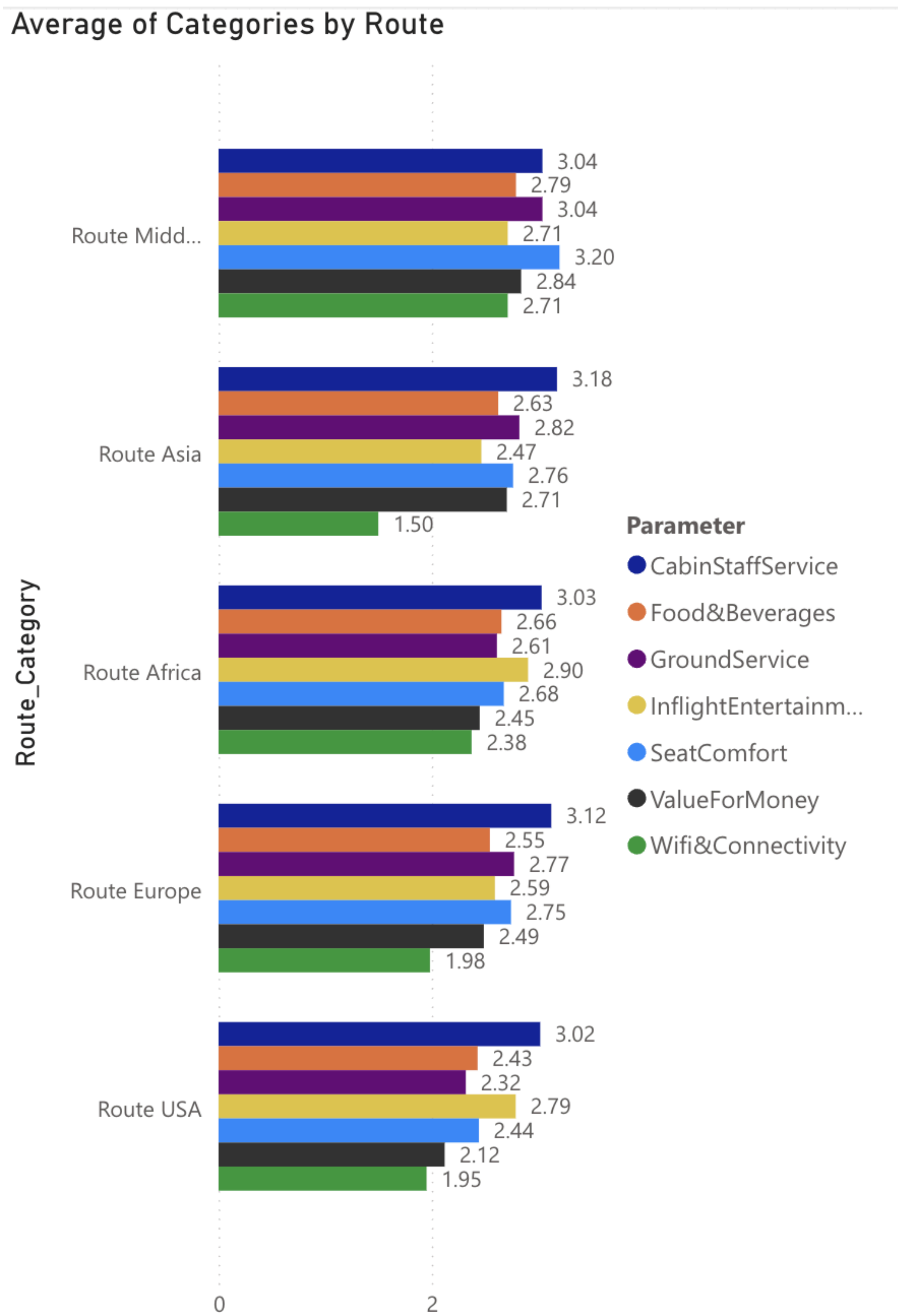

Figure 6.2.1 - Average of categories by route except for other routes

The data are inserted in table 6.2.2 to allow an easier interpretation.

	Asia	Europe	Middle East	Africa	USA
Value for money	2.71	2.49	3.20	2.68	2.44
Ground service	2.82	2.77	3.04	2.61	2.32
Cabin staff service	3.18	3.12	3.04	3.03	3.02
Seat comfort	2.76	2.75	2.84	2.68	2.44
Food and Beverages	2.63	2.55	2.79	2.66	2.43
Inflight Entertainment	2.47	2.59	2.71	2.45	2.12
Wifi & Connectivity	1.50	1.98	2.71	2.38	1.95

Table 6.2.2 - Average of categories by route except for other routes

The Middle East routes stand out as the most highly rated overall. This region recorded the highest average scores in four out of the seven parameters: ground service, food and beverages, value for money, and seat comfort. These results suggest an overall superior travel experience, likely resulting from a more consistent onboard service, efficient ground handling, and better alignment between price and perceived value. However, the total number of reviews for this route is extremely low, suggesting either a scarce usage of the instrument of reviews due to different procedures to manage the collection of data for these routes, or in general a lower propensity of travellers to leave their feedback about the experience.
Anyways, in a real-life situation, with a more precise categorization of routes with a higher number of reviews for this specific category, activities done specifically on the route operated in this region may be taken as examples to be implemented in other routes.

In contrast, United States routes recorded the lowest ratings in almost every category, particularly in ground service, inflight entertainment, seat comfort, and value for money. These figures are especially concerning given that the United States represents the second busiest route category in terms of volume. Passengers for this route are divided as in table 6.2.3.

	# of reviews	% of reviews
Business class	33	31.13%
Economy class	45	42.45%
First class	9	8.49%
Premium economy	19	17.92%

Table 6.2.3 - Reviews distribution among seat type for USA routes

In this specific case, several targeted improvements could substantially enhance passenger satisfaction and overall performance indicators. A key area of intervention is ground service, identified as a particularly weak point in customer evaluations. Enhancing this aspect through better staff training and more efficient boarding procedures could contribute to reducing friction points in the travel experience. An additional area requiring attention is seat comfort, which is closely related to the onboard environment and the condition of the aircraft interiors. The data shows that the majority of reviews for the United States route come from economy class passengers, equal to 42.45% of the total, followed by business class passengers, equal to 31.13% of the total. This distribution highlights the importance of prioritizing improvements that affect a broader base, not concentrating efforts only on a specific seat type. Again, it is important to notice that actions taken by airlines may have effects both in the short and long term. In the short term, improvements to seat comfort, such as upgrading certain seat features, can positively influence passengers' perception of service quality in both economy and business class. However, these changes are unlikely to significantly impact the overall frequency with which passengers choose to fly, particularly in the United States, where air travel is often the only viable option due to the vast distances and limited alternatives for long-distance transportation.
Moreover, the inflight entertainment system has emerged as an area where passenger expectations have risen significantly, especially for long haul international routes like those to and from the United States. Many passengers, particularly for flights where the time spent using entertainment systems is highest, expect modern platforms in line with a wide range of content, intuitive interfaces, and responsive screens. Upgrading these systems could enhance the perceived value of the flight experience and reduce dissatisfaction during long flights. Furthermore, actions taken to improve this aspect have less impact on costs for the company, but have a higher impact on the perception of improved quality for travellers.

European routes represent another core segment for international air travel, both in terms of volume, in fact it represents 81.03% of the total number of reviews, and strategic importance, given the high density of short and medium haul flights connecting key cities across the continent. From the data analyzed, European routes

exhibit intermediate scores across most service categories, without extremes of performance, but with clear areas that require targeted action. The highest score observed for this route is associated with the paramente cabin staff services, indicating that interpersonal service and interaction onboard is generally well perceived. Again in a real-life situation, activities performed in European routes associated with cabin staff services can be taken as examples to be implemented in other routes. Instead, among all the parameters, the Wi-Fi and connectivity score stands out as particularly low, suggesting that digital expectations are not being met. Airlines operating in Europe should prioritize the expansion and stabilization of in-flight connectivity, particularly by investing in more modern, satellite-based solutions, and reevaluating their pricing strategies to meet customer expectations.
Even though it is not the lowest among the routes, it is important to notice that the value for money score of 2.49 is also concerning, especially given the competitive pricing of many low-cost carriers operating in Europe. This may reflect not only price sensitivity, but also a perceived lack of justification for service quality relative to cost, especially among passengers that for travels within Europe itself have other means of transportation available, with efficiency comparable to that of an airplane. Airlines may need to rethink their service bundles, clearly communicating what is included in the fare and improving elements such as seat comfort or basic refreshments to better match customer expectations. In summary, while European routes maintain relatively balanced scores, their performance is far from optimal. Airlines operating in this region should prioritize improvements in connectivity, onboard service quality, value perception, and ground efficiency, adapting their offerings to reflect the expectations of a diverse and often highly demanding passenger base.

In conclusion, the route-based analysis underscores the variability in customer perceptions of service quality across different geographical regions, influenced by factors such as the availability of alternative transportation options, average flight duration, and culturally influenced expectations regarding air travel. This geographical heterogeneity, however, offers a strategic advantage for airlines: routes demonstrating consistently superior performance in specific metrics can be leveraged as benchmarks to guide enhancements on lower-performing routes. Moreover, routes exhibiting varying degrees of sensitivity to service modifications can be employed strategically to pilot and assess new initiatives, thereby enabling airlines to implement successful improvements in a controlled and cost-effective manner throughout their global network.

6.3 Aircraft based analysis

Another useful categorization is related to the different models of aircraft used by the company. Analyzing customer satisfaction by aircraft model offers a strategic advantage in understanding how different types of aircraft contribute to the overall passenger experience. This type of segmentation is particularly valuable for identifying performance patterns that can guide targeted improvements and operational decisions. This analysis is useful for airlines to pinpoint which aircraft types are consistently well received and which may require upgrades or reevaluation. Furthermore, this analysis becomes especially relevant when planning future investments in fleet expansion or renewal. Ultimately, a data driven approach to aircraft performance allows companies to make more informed, cost-effective decisions about where to focus their resources for maximum impact.

In figure 6.3.1 is shown the graph with the average rating for each category divided by the categorization of aircrafts performed and previously explained in chapter 5.3. In this analysis, only the following parameters were considered: inflight entertainment, seat comfort, and Wi-Fi and connectivity. The reason for this choice lies in the fact that these specific features are directly related to the aircraft model and its technical or structural configuration. Conversely, other categories such as cabin staff service, food and beverages, or ground service reflect the quality of the human service experience rather than characteristics of the aircraft itself. Including those parameters would have introduced variables influenced by crew performance and operational processes which fall outside the scope of a technical evaluation of aircraft performance and passenger experience by aircraft type. Therefore, to maintain the analytical relevance and isolate aircraft related factors, only features inherently tied to the airplane model were included. Also, data for the “various aircraft” entry of the list of aircrafts has been excluded, due to its lack of clear definition and practical actionability, as for the “other routes” entry in the route category variable.
This filtering activity led the total number of records evaluated in this specific analysis to 1603, equal to 57.5% of the total.

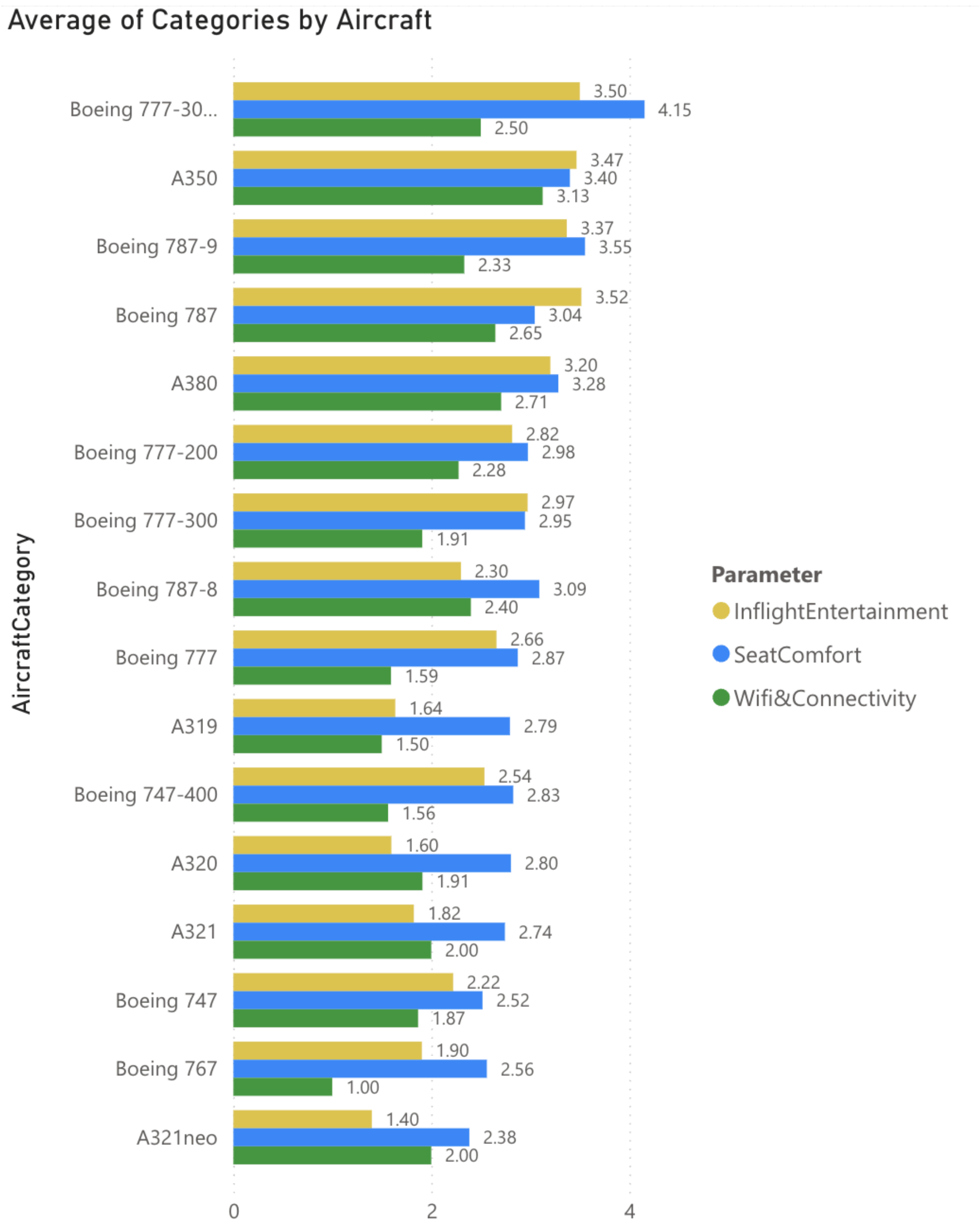

Figure 6.3.1 - Average of categories considered by aircraft except for various aircrafts

In table 6.3.1 is shown the total number of reviews and their relative percentage on the number of reviews considered excluding various aircrafts, for all the models with more than 100 reviews.

	Total # of reviews	**% when considering the total number of reviews excluding various aircrafts**
A319	107	6.67%
A320	358	22.33%
A380	165	10.29%
Boeing 747-400	180	11.23%
Boeing 777	269	16.78%
Boeing 777-200	125	7.80%

Table 6.3.1 - More evaluated aircrafts and their percentage on the total

This analysis focuses exclusively on the aircraft models that have received the highest number of reviews, more than 100 reviews, and for which data is sufficiently representative: A319, A320, A380, Boeing 747-400, Boeing 777, and Boeing 777-200. These six aircraft types together account for a total of 1.204 reviews, representing roughly 75% of all reviews that exclude uncategorized aircraft models. Their significant presence in the dataset ensures that the insights drawn are both meaningful and statistically relevant.

Among these, the A320 emerges as the most reviewed aircraft, making up 22.3% of the total considered reviews. However, this high exposure contrasts with its relatively poor performance across all evaluated aircraft-related parameters, particularly inflight Entertainment and Wi-Fi and connectivity. This aircraft is used mostly in european routes, as inferred from the graph “Number of reviews by route” in Annex B, specifically it has been evaluated 106 times in the dataset in european flights.
The contradiction between its popularity and its evaluation gives some hints about airlines' adoption of specific aircrafts. While one might assume that passenger satisfaction should play a key role in aircraft selection, the reality is far more complex. Airlines rarely choose or retire aircraft solely based on customer preferences. Instead, purchasing and operating decisions are primarily driven by economic, operational, and strategic factors. Aircraft like the A320 are widely adopted not necessarily because they offer the best passenger experience, but because they are cost-efficient, versatile, and reliable. The A320 family is optimized for short- to medium-haul routes, as said in chapter 5.3, it offers low operating costs, and is compatible with a variety of airport infrastructures. Additionally, it provides high fleet commonality with other Airbus models, which reduces pilot training costs and simplifies maintenance operations. Therefore, even if an aircraft like the A320 scores poorly in categories such as inflight entertainment or Wi-Fi and connectivity, it can still be a rational and dominant choice

from a business standpoint. These service features can sometimes be upgraded over time, while the underlying economic performance of the aircraft remains a core factor in its widespread use. This divergence between operational logic and passenger perception highlights the importance of continuous investment in the onboard experience not directly related to the infrastructure of the airplanes, such as food and beverages and cabin staff service.

Considering now the Boeing 777, including both its standard and -200 variants, stands out positively, especially in seat comfort and inflight entertainment. The standard Boeing 777 receives a particularly balanced evaluation and accounts for nearly 17% of the dataset. Its performance and usage rate make it an ideal reference point when planning enhancements on similarly operated aircraft.
From a business standpoint, these results position the Boeing 777 as a benchmark model in terms of passenger experience. A corporate team reviewing these insights might interpret the data in two complementary directions. On one hand, the strong performance of this aircraft suggests that it is already meeting customer expectations, meaning that no urgent corrective action is needed, and instead, maintenance of current standards becomes a priority. Ensuring the continuity of this positive perception through routine upgrades, staff training, and consistent onboard service quality would be advisable. On the other hand, the 777's reliable and well rated performance can serve as a reference model for targeted improvements. In fact, when aircraft manufacturing companies have to study new aircrafts models, interface with airlines to comprende their needs is fundamental. By analyzing what works well on the 777 companies could replicate successful features, both on underperforming models and on new models to be designed. Additionally, given its broad deployment and positive feedback, the 777 might also be an ideal platform for piloting new service initiatives before scaling them across the fleet.
In terms of strategic fleet planning, the 777's positive reputation strengthens its role in long-haul operations, making it less urgent to retire or replace in the short term. Instead, investment in retrofit programs could extend its lifecycle while maximizing customer satisfaction and operational efficiency.

The A380 and Boeing 747-400, still represent important parts of some long-haul fleets even though both the aircrafts are no longer produced, the A380 since 2021[16] and the 747-400 since 2023 after 56 years[17] of production. They account for more than 10.29% and 11.23% of reviews, respectively. The A380 generally scores better, especially in seat comfort, reflecting its larger cabin and modern design. This is true also when

[16] Andreas Spaeth, *Airbus A380: End of a multibillion-dollar dream*, DW, 16th of December 2021, https://www.dw.com/en/airbus-a380-the-end-of-a-multibillion-dollar-dream/a-60124995, consulted on the 18th of June 2025.
[17] Andreas Spaeth, *After 56 years, production of the Boeing 747 is coming to an end*, Aeroreport, 10th of January 2023, https://aeroreport.de/en/aviation/after-56-years-production-of-the-boeing-747-is-coming-to-an-end, consulted on the 18th of June 2025.

comparing the score for economy and business class travellers, in fact when considering the parameter seat comfort, the two types of seat score respectively 3.15 and 2.96. On the other hand, the Boeing 747-400, despite its iconic status, receives lower scores across all three parameters, indicating a possible mismatch between customer expectations and onboard experience, which can be correlated also to the fact that the main features developed for this aircraft date back to 50 years ago. As already said, especially looking at A380 features, its characteristics can be useful when evaluating new purchases and expansion of the fleet with new models of aircrafts, considering aspects which are more appreciated by customers.

The A319, which holds the smallest share among these selected aircraft, only 6.67%, also performs poorly in all parameters, particularly Wi-Fi and connectivity with an average of 1.75 and inflight entertainment with an average of 1.29. However, when looking at the graph in figure 6.3.2 it is visible that the adoption of this model of aircraft has drastically decreased from 2017, demonstrating that actions to reduce dissatisfaction of customers were already taken in the past years.

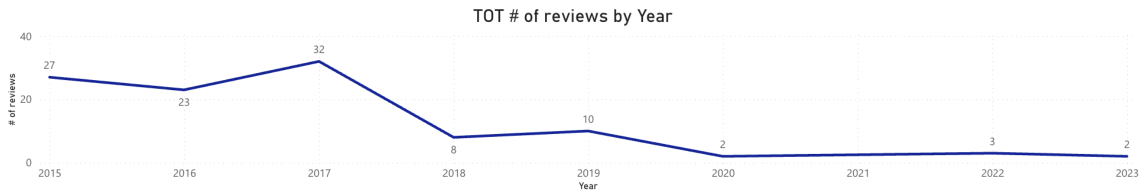

Figure 6.3.2 - # of reviews for A319 aircrafts

Given all this information, some general deductions can be made on aircraft models and their adoption. In terms of route allocation, these findings could guide the assignment of better rated aircraft to long-haul or premium-heavy routes, while deploying older or less equipped aircraft only on short-haul, low-cost, or high-frequency connections, where expectations are lower.

Regarding aircraft replacement strategies, while discontinuing low-rated aircraft could improve satisfaction, the decision must be weighed against operational and financial constraints. Aircraft retirement typically depends on factors such as age, fuel efficiency, maintenance costs, and lease agreements. However, gradual fleet modernization, prioritizing the phasing out of poorly rated aircraft and investing in refurbishing high-usage models, would align both cost efficiency and passenger satisfaction objectives over the medium term.

In conclusion, the analysis conducted at the aircraft level not only identifies areas of both strength and weakness but also informs long-term strategic planning by linking customer feedback to decisions regarding capital investments in fleet assets. Adopting such a data-driven approach has the potential to substantially improve fleet management strategies.

7. Future developments

As the current data model has demonstrated its effectiveness in supporting exploratory and comparative analysis of passenger reviews, it also reveals areas where further refinements can significantly improve its scalability, analytical depth, and long-term maintainability. While the implemented solution has provided a solid foundation for assessing service quality across routes and aircraft types, it still relies on static logic and manually curated classifications, which may limit its performance as the dataset expands or the business context evolves.

In the previously discussed chapters 5.3.1 and 5.3.2, some of the structural limitations encountered during the implementation phase have been effectively addressed by adopting a more scalable and dynamic approach to the categorization of both flight routes and aircraft. In particular, integrating structured reference datasets, enriched geospatial metadata, and standardized aircraft characteristics would allow the system to move beyond basic keyword detection or frequency-based thresholds. These enhancements would enable a more precise and automated classification of routes based on actual geographic criteria, and a more meaningful aggregation of passenger experiences across technically and operationally similar aircraft families. This would not only enhance the interpretability of the results but also support more consistent benchmarking and performance comparisons within the airline's network and fleet.
Importantly, these developments would improve not only the analytical consistency of the model but also its alignment with real-world airline practices. Route classification based on geolocation or airport metadata, and aircraft grouping based on technical specifications and internal fleet registries, reflect how airlines manage their operations and fleets in practice. As such, the insights generated from the dashboard would become more actionable for decision-makers, supporting initiatives in quality improvement, resource allocation, and long-term fleet planning.

The future robustness and scalability of the model thus depend primarily on the integration of structured and interrelated data sources. When structured in this way, where each component dynamically references standardized and authoritative information, the model evolves into a true analytical ecosystem. Within this ecosystem, customer feedback is no longer interpreted in isolation but is contextualized through shared dimensions such as geographic region, aircraft family, or service type. This structure supports more reliable, granular, and high-impact insights, and facilitates the continuous evolution of the dashboard without the need for manual adjustments.
Beyond improving performance within a single airline context, this architecture enables the model to be replicable and transferable across different organizations. By replacing or aligning the underlying reference tables with those from another airline, such as its specific route network, fleet composition, or regional segmentation, the entire

dashboard framework can be seamlessly adapted to new operational realities. This makes the system not only more powerful but also versatile and industry-ready, capable of scaling to accommodate diverse datasets and analytical requirements.

In conclusion, future developments aimed at standardizing aircraft data at the family level and dynamically classifying routes based on geographic or operational logic represent critical steps toward a more intelligent, maintainable, and business-aligned analytical model. These refinements would elevate the project from a useful visualization tool to a fully scalable business intelligence solution capable of supporting strategic decisions across multiple airline contexts. Through the integration of external data structures and advanced categorization techniques, the model would be better equipped to deliver cross-sectional insights and respond to the evolving challenges of customer experience analysis in the aviation industry.

8. Conclusion

This thesis has explored the critical role of Customer Feedback Analysis in enhancing service quality within the airline industry, focusing on how structured review data can inform quality engineering and strategic decision-making. By leveraging customer generated data collected over a nine-year period (2015–2023), the project successfully demonstrated how Business Intelligence tools, specifically Microsoft Power BI, can transform large volumes of unstructured feedback into meaningful, interactive visual dashboards.

This project work demonstrated that in the aviation sector, where feedback mechanisms are essential due to the complexity of passenger journeys and of the high number of service touchpoints, a clear structured dashboard is a useful and powerful tool in industrial frameworks. The analysis addressed specific challenges related to data collection in this industry, such as feedback fragmentation and response bias, and provided an overview of KPIs particularly relevant to airlines.

The practical core of the thesis involved the design and implementation of an interactive dashboard using Power BI. After a thorough data cleaning and transformation process, the dashboard enabled a multidimensional analysis across temporal trends, route categories, and aircraft types. This tool proved valuable not only for descriptive reporting but also for diagnostic insights that can support targeted service improvements. By enabling a detailed breakdown of performance across different dimensions, such as time periods, traveler categories, routes, and aircraft types, the dashboard revealed that the perception of service quality can significantly vary depending on contextual variables. The results suggest that operational or service enhancements should not be applied uniformly across the network but should instead be tailored to the specific challenges and expectations.
Furthermore, the analysis identified key influences on the overall customer rating, with dimensions such as value for money, cabin staff service, and seat comfort emerging as the most impactful factors. These results help define a clear path for prioritizing interventions. Airlines should focus improvement efforts on enhancing perceived service value through loyalty program adjustments, more transparent fare structures, or better economy-class comfort features, especially in the post-COVID travel landscape where expectations have shifted.

In summary, the dashboard not only visualized trends but enabled evidence-based prioritization of strategic and operational improvements, allowing airline managers to allocate resources where they are most likely to generate measurable gains in customer satisfaction and loyalty.

Strategic future developments have been proposed, such as dynamic route categorization and aircraft family grouping, to enhance the analytical robustness and operational relevance of the dashboard in a real-world context. Together, these enhancements would transform the current analytical tool into a comprehensive, adaptive, and decision-support system capable of aligning operational strategy with real-time customer insight, ultimately promoting a more agile and responsive approach to quality management in the airline sector.

Beyond its specific focus on the aviation industry, the methodology developed in this thesis demonstrates a high degree of replicability and cross-sector applicability. The end-to-end process, comprising data preprocessing, categorical normalization, KPI-driven analysis, and interactive dashboard development, can be readily adapted to other customer-facing industries that rely heavily on service quality, such as hospitality, retail, telecommunications, and healthcare. In these contexts, customer feedback is equally critical for understanding pain points, monitoring satisfaction levels, and guiding strategic interventions.
The modular structure of the Power BI dashboard also allows for easy customization to suit different types of review data, business goals, or operational hierarchies. The combination of quantitative KPI tracking with categorical segmentation, proves effective in uncovering latent patterns that would otherwise remain hidden in static reports. This makes the approach particularly suitable for organizations aiming to transition from descriptive analytics to more dynamic, decision-support systems rooted in real-time customer insight. The methodology is not only scalable but also transferable, making it a robust framework for any organization seeking to enhance its customer-centricity through the strategic use of data visualization and feedback intelligence.

In conclusion, this thesis underscores the power of customer feedback as a strategic resource and the value of data visualization tools in making that feedback actionable. The outcomes presented here not only reinforce the importance of integrating customer voices into quality management systems but also offer a replicable model for other service-oriented industries aiming to strengthen customer-centricity through data.

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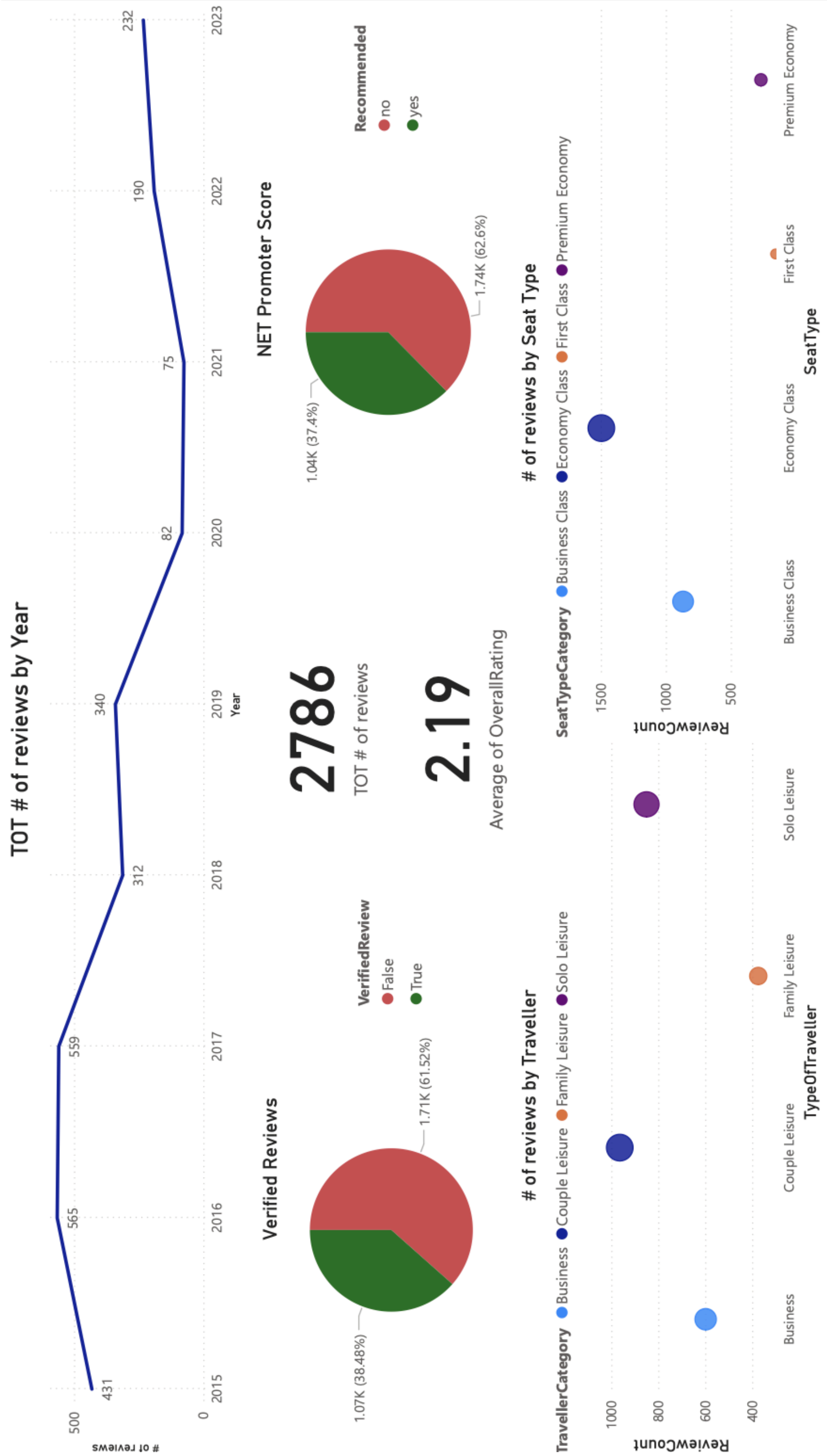
10. Annex A


TOT # of reviews by Year
# of reviews
500
0
431
565
559
312
340
82
75
190
232
2015
2016
2017
2018
2019
2020
2021
2022
2023
Year
Verified Reviews
1.07K (38.48%)
1.71K (61.52%)
VerifiedReview
False
True
2786
TOT # of reviews
2.19
Average of OverallRating
NET Promoter Score
1.04K (37.4%)
1.74K (62.6%)
Recommended
no
yes
# of reviews by Traveller
TravellerCategory
Business
Couple Leisure
Family Leisure
Solo Leisure
ReviewCount
1000
800
600
400
TypeOfTraveller
# of reviews by Seat Type
SeatTypeCategory
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Economy Class
First Class
Premium Economy
ReviewCount
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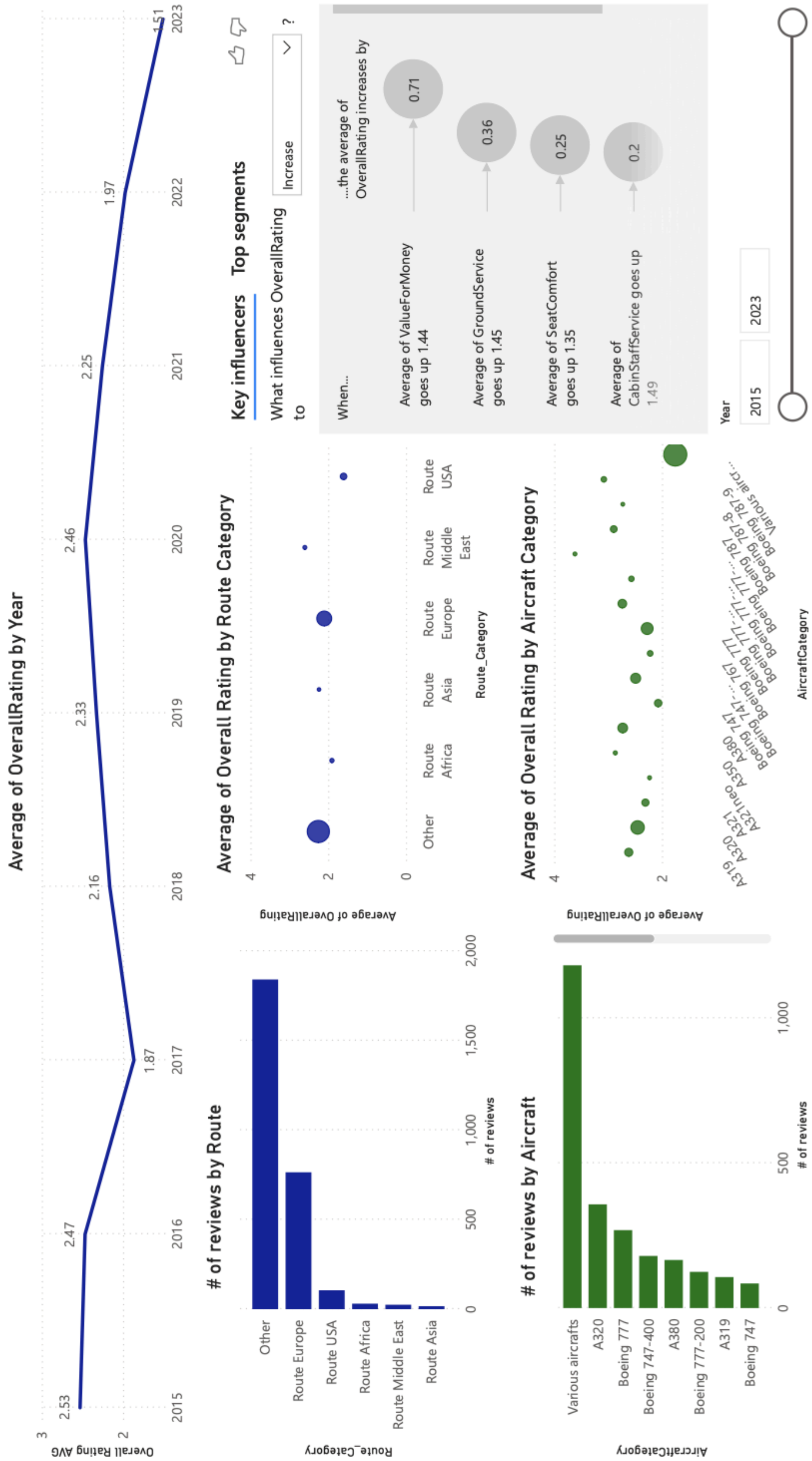
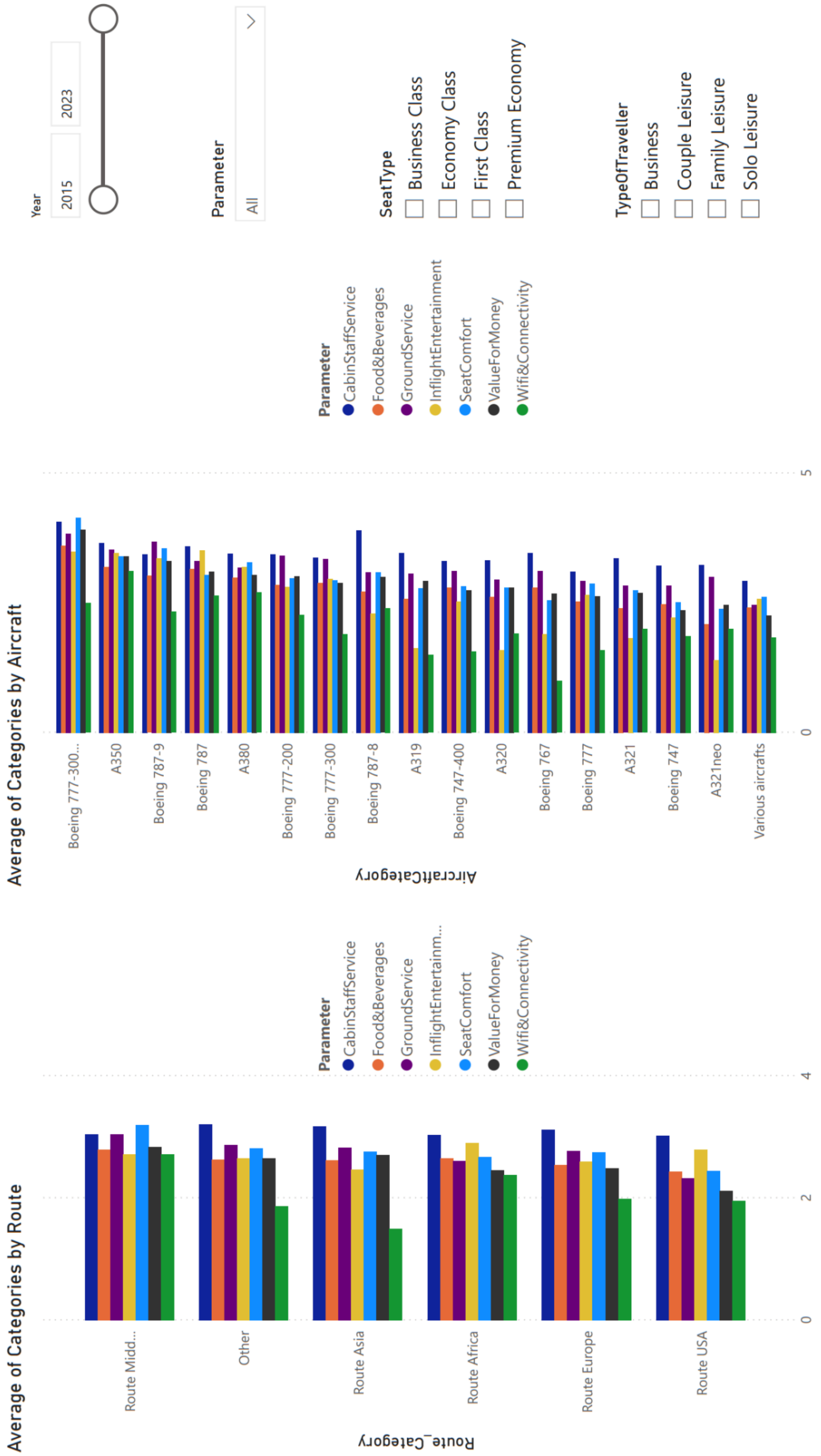
1000
500
SeatType

11. Annex B



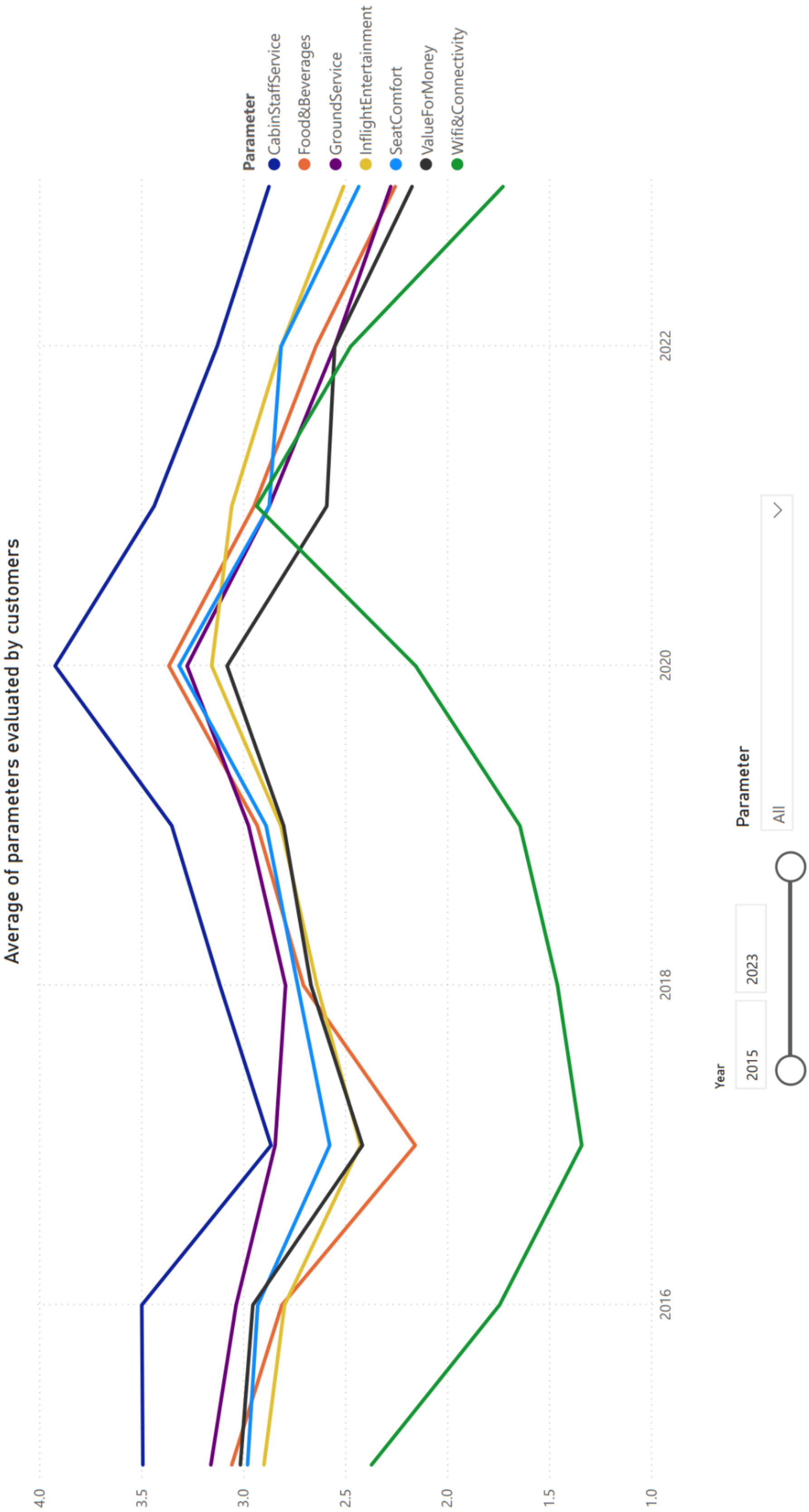
Average of OverallRating by Year
Overall Rating AVG
2.53
2.47
1.87
2.16
2.33
2.46
2.25
1.97
1.51
2015
2016
2017
2018
2019
2020
2021
2022
2023
# of reviews by Route
Route_Category
Other
Route Europe
Route USA
Route Africa
Route Middle East
Route Asia
# of reviews
Average of Overall Rating by Route Category
Average of OverallRating
Route_Category
Key influencers
Top segments
What influences OverallRating to
Increase
When...
....the average of OverallRating increases by
Average of ValueForMoney goes up 1.44
0.71
Average of GroundService goes up 1.45
0.36
Average of SeatComfort goes up 1.35
0.25
Average of CabinStaffService goes up 1.49
0.2
Year
2015
2023
# of reviews by Aircraft
AircraftCategory
Various aircrafts
A320
Boeing 777
Boeing 747-400
A380
Boeing 777-200
A319
Boeing 747
# of reviews
Average of Overall Rating by Aircraft Category
Average of OverallRating
AircraftCategory

12. Annex C



Year
2015
2023
Parameter
All
SeatType
Business Class
Economy Class
First Class
Premium Economy
TypeOfTraveller
Business
Couple Leisure
Family Leisure
Solo Leisure
Average of Categories by Aircraft
Parameter
CabinStaffService
Food&Beverages
GroundService
InflightEntertainment
SeatComfort
ValueForMoney
Wifi&Connectivity
Boeing 777-300...
A350
Boeing 787-9
Boeing 787
A380
Boeing 777-200
Boeing 777-300
Boeing 787-8
A319
Boeing 747-400
A320
Boeing 767
Boeing 777
A321
Boeing 747
A321neo
Various aircrafts
AircraftCategory
0
5
Average of Categories by Route
Parameter
CabinStaffService
Food&Beverages
GroundService
InflightEntertainm...
SeatComfort
ValueForMoney
Wifi&Connectivity
Route Midd...
Other
Route Asia
Route Africa
Route Europe
Route USA
Route_Category
0
2
4

13. Annex D



Average of parameters evaluated by customers
Parameter
CabinStaffService
Food&Beverages
GroundService
InflightEntertainment
SeatComfort
ValueForMoney
Wifi&Connectivity
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2016
2018
2020
2022
Year
2015
2023
Parameter
All