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Fasten Your Seatbelts: A Data-Driven Journey Through Airline Customer Dissatisfaction

Prof. Ernesto Cardamone

SUPERVISOR

Prof. Marco Picchierri

CO-SUPERVISOR

Chiara Mariani - 791121

CANDIDATE

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Abstract

This thesis examines the impact of extremely dissatisfied consumers on the European airline market by analyzing one-star evaluations on the Trustpilot platform. It is essential for service-oriented firms to identify the factors that lead to negative experiences, as electronic word-of-mouth (eWOM) significantly influences public perception of brands and consumer behavior. This study addresses gaps in the research by employing established concepts of consumer trust, brand equity, and service quality. The research employed Latent Dirichlet Allocation (LDA) on a dataset of over 100,000 one-star evaluations in English from 72 airlines. The seven primary factors contributing to customer dissatisfaction are: In-Flight Experience, the Check-in Process, Customer service and support, issues with booking and payment, complications with Refunds and Compensation, flight delays and scheduling conflicts, and deficiencies in Contact and Communication Channels. Communication issues were the predominant cause of dissatisfaction, succeeded by complications with refunds and alterations in scheduling. Conversely, grievances regarding onboard experiences and interactions with customer service were infrequent. This indicates that procedural issues and post-service failures are more significant in eliciting negative perceptions. I categorized airlines into three classifications to further our comprehension of how their business strategies influence these patterns of discontent: Full-Service Network Carriers (FSCs), Low-Cost Carriers (LCCs), and a newly established category termed Value Carriers (VCs). The findings indicate distinct disparities among the groups: FSCs face criticism regarding their expectations and communication during flights, LCCs are reproached for check-in issues, inflexible refunds, and convoluted booking processes, while VCs receive critiques for both, with recurrent references to delays and variable service quality. One-way ANOVA and Bonferroni post-hoc analysis revealed substantial disparities in the distribution of complaints among various carrier types. The empirical discovery of the Value Carrier category contributes to the development of a more sophisticated segmentation paradigm that transcends the conventional FSCs versus LCCs dichotomy. This study provides theoretical and practical guidance on enhancing service recovery, managing digital reputation, and optimizing strategic positioning within the airline industry.

Introduction

Have you ever felt overwhelmed by the number of reviews when trying to pick an airline? It might be hard to figure out what a brand's reputation is when there are star ratings, thorough reviews, and emotive testimonies all trying to get your attention. In the digital marketplace of today, customers are not just shoppers; they are also storytellers, critics, and people who have an impact. The airline sector is a great example of this since experiences are very personal, quite different, and very widely shared. Over the past ten years, the growth of review sites has changed the way people think about services and make travel decisions in a big way. Recent surveys show that 88% of airline passengers read internet evaluations before buying a flight (YouGov, 2023). This makes electronic word-of-mouth (eWOM) a key factor in how people see a brand. People see eWOM as more authentic, peer-driven, and emotionally resonant than traditional advertising, especially when it comes to severe user criticism. Nevertheless, a lot of academic research has looked at average sentiment or aggregated ratings instead of the most emotive and rich signals: one-star reviews. This argument is based on the desire to learn more about those signals. It looks at English-language one-star evaluations of airlines that fly in Europe that show extreme discontent. The goal is not just to list complaints but to look at what they are, how they are structured, and what they mean. This study wants to find out what makes people give bad reviews, how these complaints change between different types of airlines, and what this says about what customers expect, how much they trust the airline, and how good they think the service is. The study uses a mix of marketing and consumer behavior theories, especially those about brand equity, digital trust, and cognitive dissonance, and applies a large-scale text mining method to real-world customer data to answer these questions. By focusing on Trustpilot, a popular platform that hasn't been studied much in academia, the research gets unsolicited feedback in a way that is both new and useful in this situation. The analysis uses machine learning to find hidden patterns in dissatisfaction and gives a more in-depth look at how service failures are framed, understood, and shared online. There are four chapters in the thesis. The first part sets the stage by looking at what other research has said about how people see brands, how much they trust them, and how the role of user-generated material is changing compared to institutional signals. The second sets the conversation in the perspective of the airline industry by talking about its many parts, the importance of service quality, and the growing importance of internet reviews. The third chapter talks about the research strategy and methodology, explaining how the data was gathered, processed, and analyzed using unsupervised machine learning methods. Finally, the fourth chapter talks about what the study found and how it relates to the theoretical discussion. It also talks about what these findings mean for both marketing scholars and airline professionals.

This study intends to provide a real contribution to the study of brand perception in digital contexts by combining data-driven analysis with a solid grasp of how people think. More generally, it stresses how important it is to listen to unhappy customers, not just because it could hurt your reputation, but also because it can give you valuable information for making companies that are more trustworthy, adaptable, and believable.

Chapter 1: Introduction to Brand Perception and Trust in the Airline Industry

1.1 The Evolution of Consumer-Driven Brand Perception

1.1.1 Definition of earned media and its role in consumer decision-making

Marketing communication, in today's dynamic market, is the link between brands and their consumers, comprising every interaction that defines the relationship. Ensuring these interactions are consistent and coherent, Integrated Marketing Communication (IMC) helps to align all messages to produce a unified brand voice (Neill & Schauster, 2018). Digital technology's fast evolution has changed how companies interact with their consumers by providing fresh avenues and chances for involvement (Brockhaus et al., 2023; Tam et al., 2023). Every medium's particular qualities and reach greatly affect the efficacy of brand communications across several media channels. Evaluating the influence of various media types depends on knowledge and classification. The POEM model, which divides media into paid, owned, and earned categories, a distinction that is useful for both academic study and industry practice (Laurie & Mortimer, 2019), is a generally accepted framework.

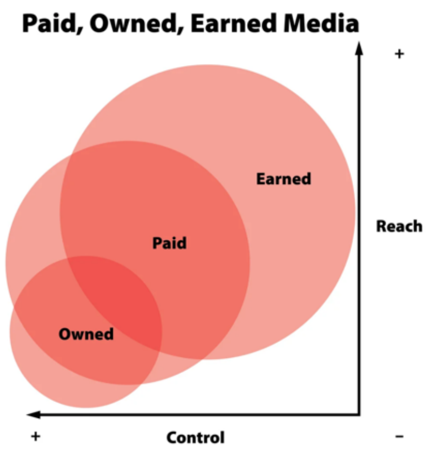


Figure 1: Mapping of paid, owned and earned media by control and reach, adapted from Felix et al. (2017)

Earned media is the natural acknowledgment a business gets from outside sources, including journalists or consumers (Stephen & Galak, 2012). Unlike paid media, which includes advertising, or owned media, which comprises company-controlled channels like websites, earned media is created by outside parties and is the least controlled, as also shown in Figure 1. Though marketers do not directly create the activity, marketing efforts can assist in producing earned media activity (Stephen & Galak, 2012). Another difference in earned media is whether it comes from conventional or social media outlets. Social earned media comes from consumers' online and offline interactions, including blog posts, social media updates, and conversations in online forums. By press coverage and promotion, professional media sources create, on the other hand, conventional earned media. Comparing the effects of conventional and social earned media, Stephen and Galak (2012) found that both affect sales; traditional earned media has the most per-event effect, while social earned media has more influence in terms of frequency.

Using natural peer-to-peer communication, word-of-mouth (WOM) is often considered one of the most powerful kinds of earned media since it shapes consumer decisions with unmatched credibility. Research indicates that WOM is more trusted than conventional advertising: 92% of consumers prefer suggestions from friends and family over branded communications (Jester Creative, 2025; Nielsen, as cited in McKinsey, 2010). Primarily because of its natural character and the reality that it is usually produced by consumers themselves, earned media is acknowledged for its major part in building confidence and credibility. Allowing consumers to *become the channel* helps to build credibility since, as Corcoran (2009) points out, they often trust third-party endorsements more than direct brand messages. Kim, Yoon, and Lee (2010) back this view by recording publicity as a more reliable and credible source than advertising. Unlike paid media, which is completely controlled by companies, earned media content's lack of control adds to its perceived authenticity (Weinberger & Brown, 1977; Arndt & May, 1981; O'Neil, Eisenmann, & Holman, 2019). Because of its natural content, earned media—often produced by public relations and word-of-mouth—is very powerful (de Matos & Rossi, 2008; Zerfass et al., 2016). Furthermore, studies show that earned media, being the most credible kind of marketing communication, can reach more people and is more successful in affecting brand loyalty and buying behavior than paid media (Lovett & Staelin, 2016; Smith, 2012). Its capacity to improve brand reputation and trust emphasizes the credibility of earned media even more, therefore underlining its importance in marketing plans meant to create strong brand awareness and advocacy (Xie & Lee, 2015).

With earned media being a key driver of trust via organic recognition, marketing communication has developed to stress authenticity and consistency across media platforms. This chapter lays the groundwork for investigating word-of-mouth (WOM), a major driver of earned media affecting consumer decisions with unmatched credibility.

1.1.2 Understanding word of mouth

One of the earliest forms of information transmission could be word of mouth (Dellarocas, 2003). Not a recent occurrence, it was the only way to sell before the arrival of mass media/printing press (Ferguson, 2008). Aristotle also addresses WoM as affected by ethos (ethical and personal appeal), pathos (emotional appeal), and logos (logical appeal) (Buttle, 1998). One of the earliest studies on how WOM affects consumer behavior characterized it as "oral, person-to-person communication between a receiver and a communicator whom the receiver perceives as non-commercial, regarding a brand, product or service" (Ardt, 1967). Since then, the definition has grown rather straightforward: an interpersonal, informal communication about products that can take the shape of goods or services (Godes & Mayzlin, 2004; Liu, 2006; Richins & Root-Shaffer, 1988).

Word-of-mouth has been shown to affect several variables, including consumer choice (Arndt, 1967; Richins, 1983), service switching (Wangenheim & Bayon, 2004), purchase decision (O'Reilly & Marx, 2011), and perception about the product/services (Sweeney et al., 2012), with brand choice facilitation (Huang & Li, 2007) for the consumers. Studies on WOM show its significant influence on listeners consistently (e.g., Arndt, 1967; Bone, 1995; Dichter, 1966; Sheth, 1971). In fact, it can be much more powerful than traditional marketing strategies in shaping consumer behavior (Katz & Lazarsfeld, 1955; Trusov, Bucklin, & Pauwels, 2009). First off, consumers are depending on other credible sources as marketing communication is losing its influence (Bughin, Doogan, & Vetvik, 2010). Especially, consumers give WOM more notice as it is seen to be credible, customized, and produced by individuals who should have no self-interest in promoting a product (Arndt, 1967; Silverman, 1997). Second, while social media is a "free" channel, traditional media costs have been rising (Fournier & Avery, 2010). WOM suggestions last longer than conventional marketing in carryover impact (Trusov, Bucklin, & Pauwels, 2009). Social media, which is seen as a less biased source of information, is likely more affected by these referrals (Dotson, 2009). Therefore, WOM is regarded as the most significant information source in consumers' purchasing decisions (Litvin et al., 2008; Jalilvand and Samiei, 2012; Lee and Youn, 2009; (Daugherty and Hoffman, 2014) and intended behavior. When we discuss intangible products that are hard to assess before use, this impact strengthens. Given that WOM can benefit or harm companies, organizations are treating it seriously (Shi et al., 2016). For instance, Liu (2006) showed that online movie reviews could greatly account for box-office income.

1.1.3 The transition to electronic word of mouth

Consumers shared each other's product-related experiences via conventional WOM (Yang et al., 2012) before the Internet's spread; however, the rapid development of technology has given consumers many chances to engage with companies and other consumers across several channels, including social media, therefore enabling them to generate electronic word of mouth (e-WOM) (Ai et al., 2022; Lai et al., 2022; Lee et al., 2022; Ngarmwongnoi et al., 2020). Put another way, word of mouth (WOM) and opinions about goods or services shared with others have expanded into e-

WOM formats, including electronic bulletins, newsgroups, blogs, online discussion forums, reviews, and networking sites (Hussain et al., 2020).

Among the many words that have been coined and used interchangeably to describe e-WOM are web-of-mouse, word of mouse, Internet word of mouth, and consumers' reviews (Shin, 2007). Remarkably, Litvin et al. (2008) proposed one of the most complete definitions of eWOM as "all informal communication via the Internet addressed to consumers and related to the use or characteristics of goods or services or the sellers thereof." Moreover, they also proposed a typology illustrated in Figure 2. Indeed, eWOM can consist of online comments or opinions (Thorsten et al., 2004; Pantano and Corvello, 2013), blogging (Thorson and Rodgers, 2006), product information (Bickart and Schindler, 2001), reviews (Zhang et al., 2009), and emails (De Bruyn and Lilien, 2008).

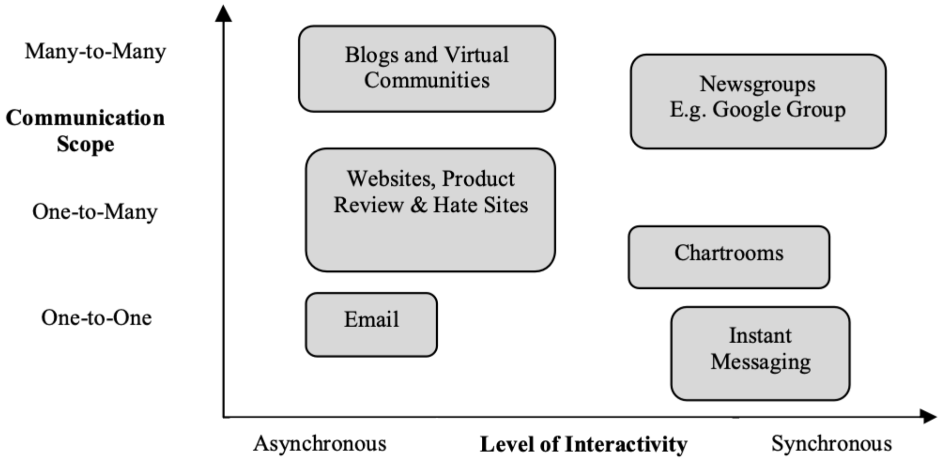


Figure 2: A typology of electronic word of mouth channels (Litvin et al., 2008)

Although e-WOM affects consumer behavior similarly to conventional WOM, it is vastly different in scale and speed, as explained in Figure 3 below. Unlike conventional WOM, e-WOM enables many-to-many communication and lets information spread far more quickly (Gretzel & Yoo, 2008; Cantallops & Salvi, 2014).

	WOM	eWOM
Credibility	The receiver of the information knows the communicator (positive influence on credibility)	Anonymity between the communicator and the receiver of the information (negative influence on credibility)
Privacy	The conversation is private, interpersonal (via dialogs), and conducted in real time	The shared information is not private and, because it is written down, can sometimes be viewed by anyone and at any time
Diffusion speed	Messages spread slowly. Users must be present when the information is being shared	Messages are conveyed more quickly between users and, via the Internet, can be conveyed at any time
Accessibility	Less accessible	Easily accessible

Figure 3: Differences between WOM and eWOM (Huete-Alcocer, 2017)

Its availability and reach are among the main benefits of e-WOM. Consumers today depend much on online reviews, sometimes believing them as much as suggestions from family and friends (Nieto et al., 2014). For companies, e-WOM provides a great chance to evaluate the influence of online reviews and grasp customer motivations. This knowledge helps businesses to change their marketing plans to better fit consumer demands (Cantallops & Salvi, 2014). Furthermore, e-WOM lets companies interact with consumers, create an online presence, and shape buying intentions (Halim et al., 2022; Muritala et al., 2020).

E-WOM has a major impact on consumer decision-making. Research has demonstrated that sales are directly affected by online reviews (Chevalier & Mayzlin, 2006; Dellarocas et al., 2007; Duan et al., 2008; Liu, 2006). Furthermore, almost 70% of internet users believe in e-WOM (Nielsen Global Online Consumer Survey, 2009), therefore stressing its relevance for advertisers. For businesses, using technology to disseminate views on goods or services is both a chance and a difficulty since it is a factor they cannot completely regulate. Especially, negative e-WOM often spreads faster than positive e-WOM (Donthu et al., 2021).

Ultimately, user-generated e-WOM has turned into a powerful weapon for disseminating product or service knowledge. It offers a forum for people to voice neutral, good, bad, objective, or subjective views (Filieri et al., 2018; Garg & Pandey, 2020; Lee & Youn, 2009). Understanding the dynamics of e-WOM is vital for companies trying to use its advantages properly, as it shapes consumer behavior.

1.1.4 Overview of official quality recognitions and their intended role in brand credibility

Although electronic word of mouth (e-WOM) is a major influence on consumer perceptions via peer-driven referrals, it is not the only element fostering market confidence. Powerful trust signals are official acknowledgments, including industry awards like the Malcolm Baldrige National Quality Award, certifications like ISO 9001, and regulatory seals like USDA Organic.

Figure 4: Examples of official quality certifications: ISO 9001:2015 and USDA Organic

These endorsements from third-party organizations confirm a brand's dedication to quality, safety, or ethical standards, therefore bridging the divide between what businesses say and what customers think (Akerlof, 1970).

Certifications increase brand trust by means of their reduction of uncertainty: the conviction that a brand can and will fulfill its promises (Erdem & Swait, 2004; Baek et al., 2010). For high-stakes purchases, such as organic food or pharmaceuticals, certifications are especially useful in lowering perceived risks. USDA Organic labels, for instance, allay worries about pesticide use and help to shape purchase choices (Thøgersen et al., 2010; Verbeke, 2005). Building trust in healthcare depends on certifications such as FDA approval; 63% of consumers give certified products top priority because of safety issues (Verbeke, 2005). Apart from retail, certification systems reach into sectors including business-to-business trade, labor markets, and services including medical care and auto repair. Studies show that certification raises the probability of selling a product by 7%, stressing its relevance in all sectors (Elfenbein et al., 2014).

Certifications also enable companies to be more visible in competitive sectors. Often letting companies charge more by indicating better quality, awards like "Product of the Year" increase visibility on store shelves and inspire customers to sample new products (Larceneux et al., 2012).

Certifications like CE marks or Halal logos help brands negotiate cultural and legal variances in international markets by showing compliance with worldwide standards (Steenkamp, 2019).

When deciding, consumers actively look for these trust signals; 82% say they look for certifications when purchasing unknown brands (Nielsen, as cited in Mohan et al., 2020). Conversely, the lack of anticipated quality seals might have undesirable effects: research indicates that 71% of consumers forsake products lacking these endorsements (Boulding & Kirmani, 1993).

Consumers use certifications and other quality disclosures to navigate their decisions from cradle to grave. These systems eliminate uncertainty and handle "lemons" issues—cases where consumers find it difficult to tell high-quality products from bad ones—across a broad spectrum of markets, whether one is selecting a hospital for medical treatment or organic produce (Dranove & Jin, 2010). In the end, certifications are not only instruments for lowering risk; especially in markets where quality is hard to evaluate directly, they are fundamental to developing trust and influencing consumer behavior in both local and worldwide settings when combined with e-WOM.

1.2 The Influence of Online Reviews on Brand Perception

1.2.1 How WOM and online reviews shape consumer attitudes

Negative word-of-mouth (NWOM) communication has been defined as "interpersonal communication among consumers concerning a marketing organization or product which denigrates the object of the communication" (Richins, 1984). Extensively researched for its significant effect on consumer perceptions and behaviors, this form of communication is based on Arndt's (1967) basic definition of word-of-mouth (WOM) and Weinberger, Allen, and Dillon's (1981) conceptualization of negative information.

Studies show that WOM is essential in forming consumer attitudes (e.g., Arndt, 1967; Bone, 1992; Laczniak, DeCarlo, & Ramaswami, 2001; Richins, 1983, 1984). Because they account for a great spectrum of human behavior and reactions to marketing stimuli, attitudes are seen as a vital concept in behavioral research (Peter & Olson, 1990). In this framework, NWOM has been demonstrated to have especially negative consequences on consumer attitudes and buying intentions. Arndt's (1967a) groundbreaking research, for instance, found that under test market conditions, exposure to negative WOM greatly lowered short-term purchase activity for a new food product. This result emphasizes the unequal character of WOM impact: whereas positive WOM (PWOM) can increase purchase probability, NWOM is usually more powerful in discouraging it.

The power of NWOM lies in its perceived diagnosticity—negative information is seen as more credible and risk-relevant than positive information (Herr et al., 1991; Richins, 1984). When assessing products or services, consumers often give negative information more weight since it indicates possible hazards or failures. In service settings—for example, healthcare or automotive repairs—where quality is subjective and post-purchase assessment is naturally difficult, this impact is especially strong (File & Prince, 1992; de Matos & Rossi, 2008). Consequently, NWOM increases perceived risks, such as financial loss or functional inadequacy—which mediate the connection between NWOM exposure and reduced purchase intent (Laczniak et al., 2001; East et al., 2008).

Empirical research also draws attention to NWOM's unequal reach in comparison to PWOM. Dissatisfied consumers usually tell more people about their bad experiences than happy ones do about their good ones. For example, TARP (1986) discovered that unhappy consumers tell their stories to twice as many people as happy ones do. Likewise, Kotler (1991) found that unhappy consumers typically spread NWOM to eleven friends, whereas happy ones only share PWOM with three. Hart, Heskett, and Sasser (1990) supported this conclusion by proposing that people with memories of poor service tell their stories to about eleven people as opposed to six for those with positive recollections. Such results show the unequal distribution of WOM and its consequences for brand image.

NWOM's emotional intensity increases its influence even more. Negative experiences can lead to intense feelings like anger or frustration, which makes it more probable that one would share these events with others (Kalamas et al., 2008; Wetzer et al., 2007). Emotional resonance not only increases the appeal of NWOM but also makes it more memorable for the sender and the receiver. This is consistent with Richins' (1983) studies, which found that unhappy consumers reported an average of five others about their negative interactions with apparel products. The effect of NWOM, therefore, is not consistent in all situations; it varies according to various moderating elements. Pre-existing brand knowledge can help to offset NWOM's negative consequences. According to Herr et al. (1991), previous favorable perceptions of a brand lessened the impact of NWOM, especially when conveyed via impersonal media like print. Furthermore, attribution patterns are important in deciding how people react to NWOM. NWOM's detrimental impact on consumer perceptions is greatly reduced when product failures are ascribed to external elements—such as user error or situational causes—rather than brand responsibility (Ramaswami, 2001; Newman, 2003).

Although NWOM may have negative consequences on consumer attitudes and behaviors, proactive measures like good complaint management and service recovery can help to offset it. Maxham's (2001) study showed that addressing customer complaints can turn unhappy consumers into advocates producing PWOM rather than NWOM. Orsingher et al. (2010) underlined in like manner that open communication during crises lowers brand blame assignment and aids in maintaining consumer confidence.

1.2.2. The amplification effect of NWOM in digital environments

The way people express opinions has been transformed by the growth of the Internet from conventional face-to-face contacts to a broader, albeit less personal, digital format. Primarily via online review sites, where consumers freely express their experiences and views about products and brands, this digital word-of-mouth—known as electronic word-of-mouth (eWOM)—occurs.

Online customer reviews have surely become a vital component of the decision-making process today, therefore greatly affecting product sales and consumer behavior. A 2015 poll by Zhong-Gang et al. makes this obvious: almost 60% of consumers look at online reviews every week; a staggering 93% believe these reviews will help them improve their buying decisions, lower possible risks, and focus their shopping options. Vimaladevi and Dhanabhakyam (2012) underline even more that many customers depend on reviews and consult them often before making their buying decisions. Many studies show that online reviews significantly influence consumer purchasing choices (Zhang et al., 2014; Zhong-Gang et al., 2015; Ruiz-Mafe et al., 2018; Von Helversen et al., 2018; Guo et al., 2020; Kang et al., 2020; Wu et al., 2021). For instance, Lackermair et al. (2013) showed that ratings and reviews are major information sources for consumers. Likewise, Bae e Lee (2011) discovered that reviews published in online communities are seen as particularly credible, especially when customers want knowledge about current products. Because they reflect real user experiences rather than marketing material, consumer reviews are usually relatable and trustworthy to consumers, therefore significantly enabling their decision-making process (Mudambi & Schuff, 2010). Research by Bataineh et al. (2015) supports previous eWOM literature results, stressing that the quality of online reviews is the most important factor influencing consumers' purchase intentions (Do-Hyung et al., 2007; Cheung and Thadani, 2009). Likewise, consumer choices are greatly influenced by elements such as review credibility (Mangold et al., Faulds, 2009) and number (Do-Hyung et al., 2007; Lee et al., 2008). Their perceived utility is one of the key factors driving the increasing influence of evaluations. Reviews give consumers confidence and security in their buying choices when they find them useful (Lin, Wu and Chen, 2013). This is particularly true given that online reviews usually originate from other consumers who have actually used the product, therefore offering insights usually lacking in sellers' official descriptions (Baek et al., 2012). For instance, Ye, Law, and Gu (2009) found that favorable online reviews greatly increase hotel reservations in comparison to negative ones; this pattern was also verified in research of online bookstores

(Chevalier et al., Mayzlin, 2006) and restaurant popularity (Zhang et al., 2010). These results emphasize that the tone of reviews—whether positive or negative—directly affects consumer behavior, especially for experience-oriented products like hotels and restaurants, which are more difficult to assess in advance (Bronner and de Hoog, 2010). Often, consumers use these shared experiences as standards (Harrison-Walker, 2001).

Interestingly, negative reviews (NWOM) often have an even greater influence than positive ones (Herr, Kardes and Kim, 1991). According to prospect theory, the dissatisfaction of experiencing a loss outweighs the satisfaction gained from a comparable positive experience. Negative comments, therefore, tend to affect people's impressions and intentions more strongly than positive ones. Research shows time and again that negative comments are viewed as more trustworthy, useful, and convincing, therefore significantly influencing views about businesses and their offerings (Herr et al., 1991; Laczniak et al., 2001; Lee and Song, 2010; Park and Lee, 2009). But, depending on the situation, negative reviews have different effects. Sen and Lerman (2007) noted that negative comments on hedonic (pleasure-oriented) items are seen as less helpful than on utilitarian (practical) products. When judging items in line with aspirational or promotion-oriented objectives, Zhang et al. (2009) found consumers often prefer positive evaluations; yet they prefer negative reviews when items are linked with prevention-oriented objectives. Guo et al. (2020) underlined as well that nice evaluations usually result in more purchase probability than negative ones.

1.2.3 Platform-specific differences in review dynamics and credibility

Many times, modern consumers interact with several internet sites to find and distribute electronic word-of-mouth (eWOM) communications (Cao et al., 2018; Ismagilova et al., 2017). Usually, these platforms fall into five separate groups: blogs, e-commerce sites (like Amazon), dedicated review websites, online discussion forums, and social media (e.g., Facebook, Twitter). Every platform category directly shapes consumer perceptions of the credibility and influence of reviews, therefore influencing their attitudes towards the material itself (Gvili & Levy, 2016).

Especially in terms of review ratings, notable variations have been found across these sites. For example, with an average difference of roughly 0.7 stars, restaurants regularly score better on Google Maps than on Yelp; chain restaurants see an even greater difference (Li & Hecht, 2021). Such variations have obvious financial consequences shown by the discovery that even a small half-star rise in Yelp ratings may increase restaurant sales by around 9% (Luca, 2016). Site policies, technical characteristics, treatment of false reviews, and their target audiences help to explain these platform differences. Open review sites like TripAdvisor let any user post free comments; closed platforms like Booking.com follow a more rigorous invitation-only policy, guaranteeing reviews originate from confirmed consumers (Kirilenko et al., 2023). These various strategies influence social interaction, accessible reviewer data, and general content richness, so influencing consumers' confidence and perceived review credibility (Levy & Gvili, 2015).

The platform kind also influences consumer interaction. Social media and discussion forums usually provide richer, more interactive experiences (Chen et al., 2011; Lima et al., 2019), and therefore, their reviews tend to have stronger social and normative influence than reviews on e-commerce platforms (Yan et al., 2018). Third-party review websites and independent forums are also seen as more credible than seller-controlled sites since they are seen as unbiased and lack direct seller influence (Cao et al., 2018; Hong et al., 2017; Tsao & Hsieh, 2015). Research has revealed notable differences across review sites in certain sectors. For example, studies on the hospitality industry have shown different review dynamics among websites, including TripAdvisor, Expedia, and Yelp (Xiang et al., 2017). Often, Yelp has a typical U-shaped or saddle-shaped rating distribution that highlights people's propensity to mostly report either very good or very bad experiences (Zervas et al., 2021). Though common on sites without corrective mechanisms, such distributions highlight consumer biases toward voicing polarized views (Kirilenko et al., 2023). Policies on anonymity and review authenticity cause more disparities between platforms. More negative and aggressive reviews are linked to greater reviewer anonymity, which is typical on open platforms, according to Deng et al. (2021). On the other hand, closed platforms that verify reviewer identity or encourage thorough comments tend to show more balanced, positive reviews. For example, websites such as Booking.com directly request thorough customer feedback, so lowering negative biases and improving general credibility (Kirilenko et al., 2023).

Reviews' credibility is also closely related to the perceived reputation and trustworthiness of the platform itself (Chih et al., 2013; Lee et al., 2011; Lee & Shin, 2014). In perceived credibility, independent, consumer-driven platforms regularly outperform corporate-run or seller-based channels (Bae & Lee, 2011; Tsao & Hsieh, 2015). Users believe independent assessments more than possibly prejudiced corporate communications, which creates this credibility gap (Senecal & Nantel, 2004; Truong & Simmons, 2010).

Finally, consumers' perceptions are greatly shaped by the entertainment value and knowledge of platforms. Platforms that enable richer content types, like social media and blogs, are seen as more entertaining, which lowers annoyance and boosts participation (Kaplan & Haenlein, 2010; Schulze et al., 2014). By comparison, basic text-based channels like SMS or short comment boards are usually seen as less interesting and less valuable (Gvili & Levy, 2015).

1.3 The Role of Official Quality Recognitions in Shaping Brand Equity

1.3.1 The brand equity framework and its connection to trust

Building on the findings of the previous subchapter on electronic word-of-mouth (eWOM), it is time to investigate another basic motivator of consumer behavior and brand perception: brand equity and its link with consumer trust.

Although eWOM platforms greatly affect brand reputation online and consumer perceptions (Babić Rosario et al., 2016; Cheung & Thadani, 2012a, b), it is crucial to understand that the efficacy of such online reviews and interactions finally depends on consumers' current trust in a brand (Gvili & Levy, 2016). Trust is the basic pillar that not only amplifies the influence of good eWOM but also reduces the negative consequences of critical comments (Cao et al., 2018). Numerous studies have shown that trust is a key factor influencing consumer-brand interactions. Morgan and Hunt (1994), Geyskens and Steenkamp (1995), and other academics underline trust as both a precursor and a result of effective brand interactions. Trust affects not only quick buying choices but also long-term brand loyalty by means of consumers' impressions of brand sincerity and dependability (Chaudhuri & Holbrook, 2001).

A foundation of brand equity is trust, which reflects consumers' belief that a brand will consistently provide value and keep its promises (Delgado-Ballester & Munuera-Alemán, 2005). Brand equity is mostly in the impressions, memories, and feelings people connect with a brand, which influences their buying behavior (Srivastava & Shocker, 1991; Keller, 1993). From a managerial perspective, brand equity directly converts into tangible benefits—greater sales volumes, premium pricing power, and more consumer loyalty (Aaker, 1991; Bello & Holbrook, 1995). Although brand equity can be measured financially, it is essentially an intangible asset showing the close ties consumers build with brands (Aaker, 1991; Yasin et al., 2007). Trust is absolutely central to these relationships—and therefore the equity itself (Morgan & Hunt, 1994; Geyskens & Steenkamp, 1995). Delgado-Ballester and Munuera-Alemán (2005) argue that trust essentially defines consumers' perceptions of brand responsiveness, honesty, and dependability. They underline that trust not only results from satisfaction with past brand interactions but also shapes future consumer behavior, therefore strengthening brand loyalty and improving brand equity (Ganesan, 1994; Selnes, 1998). Shaped by accumulated experiences, interactions, and perceptions, this trust develops slowly (Garbarino & Johnson, 1999; Keller, 1993). Every consumer interaction—whether direct or indirect (via advertising or word-of-mouth)—is therefore critically important (Krishnan, 1996; Dwyer et al., 1987). Dynamic and slow to develop, it can quickly erode if the consumer's expectations are not met or trust is broken. A brand's pricing strategy provides a revealing illustration: customers might first see higher costs as signs of better quality, therefore strengthening trust; but, if a brand drastically raises prices without matching value, trust starts to fade, usually destroying brand equity (Ambler, 1996).

Furthermore, brand love and loyalty are closely related to trust. Research by Carroll and Ahuvia (2006) and Batra et al. (2012) shows how trust not only predicts but also strengthens emotional ties, therefore promoting brand love and customer loyalty. User ratings and reviews provide trust in digital settings, especially for peer-to-peer digital brands like Airbnb or Uber, which is essential (Hamari et al., 2016; Telles, 2016). This trust system shows the great consequences of trust inside digital brand equity frameworks by greatly influencing consumer choices and brand reputation.

1.3.2 Influence of industry awards and certifications on corporate reputation

Industry awards and certifications are important indicators of quality and trust in marketing, therefore greatly influencing a brand's reputation. These awards could be classified as endorsements from third-party organizations (TPOs). Through a process of impartial and objective assessment, including but not limited to independent organizations, newspaper editorials, consumer magazines, business press, or analysts, TPOs are autonomous entities providing consumers' product reviews and trustworthy company information (Skard & Thorbjornsen, 2014; Vaid & Ahearne, 2018; Wang & Muehling, 2012). Typically found in advertisements to boost the credibility and persuasiveness of the material provided, TPO endorsements are based on independent source information (Albersmeier et al., 2009). According to source credibility theory (Berlo, Lemert, & Mertz, 1969), how credible the source is determines how persuasive a communication is (Lowry, Wilson, & Haig, 2014).

The signaling theory holds that signals can act as visible demonstrations of unobservable qualities, such as intentions, motives, behaviors, or performance, thereby reducing information asymmetries between two parties (Connelly et al., 2011; Spence, 2002; Hetze, 2016; Moratis, 2016). The party holding information about quality or intention - the sender - sends signals to the less knowledgeable party, or the receiver (Lansing et al., 2019). Signaling theory emphasizes purposely transmitting good information to express good qualities (Connelly et al., 2011). In this case, third-party certification labels such as Fair Trade or ISO standards can serve as signals by clearly linking a brand with particular criteria, therefore distinguishing the item and boosting consumer confidence in its quality. When consumers cannot directly see product qualities, these awards act as external signals, much like price or brand name, that help them infer quality and credibility.

These theoretical ideas are backed by empirical research. Rindova et al. (2005) discovered that media rankings - certifications from institutional intermediaries - and certifications of accomplishment affect corporate reputation, therefore enabling a company's notable competitive edge. Certainly, a company with a good corporate reputation can obtain significant financial and non-financial rewards (Feldman, 2014; Walsh et al., 2009), including encouraging good word-of-mouth behavior (e.g., Groenland, 2002). A company's reputation might be a quality promise for consumers. For example, Fortune's list "America's Most Admired Corporations" has grown to be a frequently checked indicator of organizational reputation (Roberts & Dowling, 2002).

A study done by Hasan and Hossain (2021) showed, further underlining these impacts, that industry accolades increase brand perceived quality and consumer confidence. Their findings offer empirical proof that a corporate recognition award increases consumers' confidence in a company, as well as their happiness, loyalty, and word-of-mouth recommendations. Examining a highly awarded financial brand (Franklin Templeton Investments), Wang and Lee (2016) discovered that using its accolades in marketing improved the brand's perceived quality and image, which then increased brand trust and purchase intention among investors. Since a good brand image increases consumer trust and purchase probability, the writers believe companies should highlight their accolades in communications to strengthen their brand image and perceived quality.

Certifications yield similar results. A study of ISO 9000 quality certification in the service sector, for example, revealed that certified companies have better perceived service quality and enhanced corporate image in the eyes of consumers (Caro and Garcia, 2009). These results imply that official certifications are guarantees of quality, therefore reflecting a more favorable view of the brand's competence and dependability. Researchers have noted an increase in brand image and perceived integrity even in particular settings such as halal product certification. For instance, Souiden and Jabeur (2015) discovered that halal certification significantly enhances the brand image among Muslim consumers by indicating the product's compliance with rigorous ethical and quality criteria. Results from the Marschlich and Hurtado (2024) study, likewise, in the framework of corporate social responsibility (CSR), showed that external CSR certifications raise the perceived authenticity and credibility of CSR communication and lower people's CSR skepticism.

1.3.3 The difference between official recognitions and user-generated feedback

Trust is fundamental in forming consumer choices, so it is crucial to know how people view the credibility of various information sources, particularly institutional rankings and user-generated content (UGC). Typically, official awards and certifications like industry honors are good indicators of credibility that boost consumer confidence by indicating compliance with consistent and demanding standards (Rindova et al., 2005; Hasan & Hossain, 2021; Wang & Lee, 2016). Digital platforms and electronic word-of-mouth (eWOM), driven mostly by consumers' first-hand experiences, however, offer a different yet interesting kind of brand assessment (Babić Rosario et al., 2016; Cheung & Thadani, 2012a, b).

Empirical research backs up this dynamic. Essig (2024) underlines that while user-generated reviews may have more influence due to their perceived authenticity and thorough experiential material, institutional accolades mostly indicate dependability and knowledge. When judging subjective qualities like customer care and tailored service, this impact is especially strong (Genc & Naik, 2023). User-generated content also has difficulties, though, especially in terms of credibility from false reviews and prejudices that could compromise general brand equity and consumer confidence (Berthon & Pitt, 2018).

Brands feel a strong synergy when institutional accolades and user-generated comments complement one another, therefore greatly boosting consumer confidence and strengthening brand equity. On the other hand, differences between these two points of assessment cause consumer uncertainty and cognitive dissonance, therefore driving them to resolve contradictory data (Essig, 2024; İdemen & Elmadağ, 2024). Depending on the particular situation, their personal trust levels, or the kind of product involved, such discrepancies could cause consumers to delay buying decisions or force them to give one source priority over the other (Essig, 2024; Lee & Hong, 2019).

Ultimately, companies that want to manage brand equity well must accept and match institutional honors with real customer experiences, therefore protecting brand reputation and guaranteeing long-term consumer trust (Genc & Naik, 2023; Marschlich & Hurtado, 2024).

1.4 Reconciling Conflicting Brand Signals

1.4.1 Factors Contributing to Conflicting Brand Perceptions

Consumers nowadays frequently come across contradictory brand signals—for instance, fantastic user-generated reviews versus harsh expert ratings or official accolades, or mixed reviews on the same platform for the same product—causing mixed impressions of the same brand.

Many studies show how such contradictory signals appear and influence brand perceptions. In fact, He (2016) showed that consumers' brand attitude is greatly harmed by contradictory information and that brand commitment moderates this effect. Conversely, Cheung et al. (2009) demonstrated that the apparent reliability of the information is strengthened by consistent recommendations across several user reviews, therefore boosting its persuasive power in forming consumer attitudes. Research by Aktar et al. (2019) in the online hospitality sector reveals that when a hotel's reviews are a mix of extremely positive and very negative views, consumers feel attitudinal ambivalence and uncertainty, which cause psychological discomfort and uncertainty. Ambivalent attitudes have independent components of both good and bad rather than general unidimensional assessments (Kaplan, 1972; Priester & Petty, 1996, 2001).

Conflicts can also arise between peer review and expert review, as shown by Tat Keh and Sun (2018). They found that for experience services (e.g., hotels, restaurants), consumers tend to give more weight to the opinions of peers (other customers) than those of experts or official sources, as shown in Figure 5 below. This means that an award or a review by an expert will have less emotional impact than a string of negative customer reviews, at least for services whose quality the user feels able to judge personally. For credence services (where it is difficult to judge quality by oneself, e.g., safety or technical reliability), the opposite happens: the voice of the expert counts more because the consumer does not fully trust his or her own judgment.

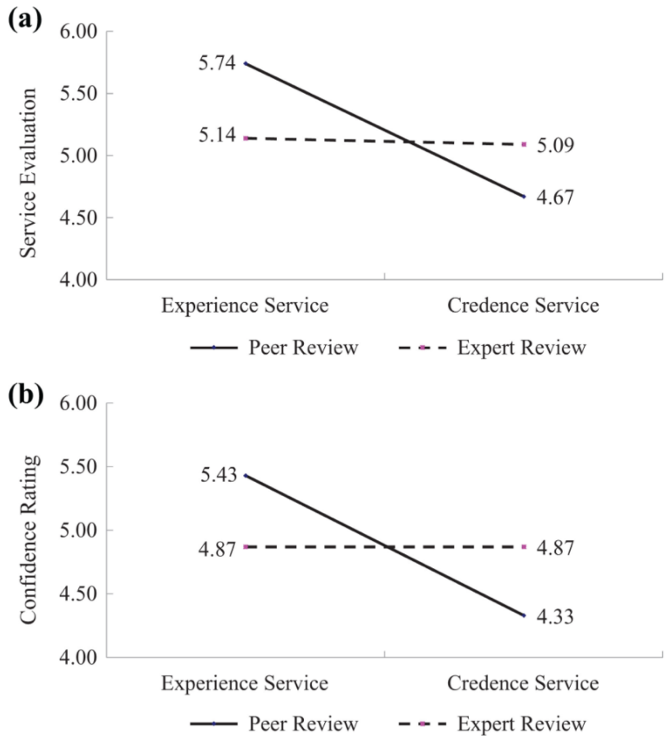


Figure 5: Interaction effect of information source and service type (Tat Keh et Sun, 2018)

Usually, a large majority of peer reviews has a stronger impact on consumer decisions than a single outlier review, but a single expert review can dominate the crowd if it contradicts them (Naujoks and Benkenstein, 2020). This suggests that source knowledge is one of the qualities people depend on, and it can be assessed from the quantity of written reviews, the number of votes (suggesting the review's usefulness), or badges given (Baek et al., 2012; Cheung et al., 2008; Watts and Zhang, 2008). Especially for experience services, knowledge is a useful factor for assessing the relevance of a review message (Racherla and Friske, 2012).

Other elements have to do with the material and consistency of the data. A frequent cause of contradictory brand impressions is valence inconsistency in eWOM, or the degree to which the sentiment—positive or negative—of a review corresponds with that of others. Reviews with consistent valence were found by Quaschning et al. (2014) to be more beneficial than those that differed. Put another way, opinion congruence helps to be useful and steady emotional tone across reviews increases their influence. Interestingly, not all inconsistency is bad: a study carried out by Xian et al. (2023) found that when reviewers disagreed on particular product characteristics (each stressing different pros and cons), consumers really felt the information was more informative, which boosted their confidence in making a decision. By contrast, bold disagreements in general ratings (some reviews praising the product while others criticize it) or a large number of polarized opinions tended to reduce perceived informativeness and raise uncertainty (Xian et al., 2023). A review that contradicts the overall feeling might also draw excessive notice; López-López and Parra (2016) found that a review with a valence inconsistent with the average was often regarded as very useful and convincing to readers. This implies that consumers may process more deeply and notice conflicting signals.

Schlosser (2011) also looked at intra-review consistency, particularly the relationship between a reviewer's star rating and their written argumentation, and found that when the justification (text) supports the rating, reviews are more convincing. Baek et al. (2012) found, to reinforce this case even more, that greater the degree of rating inconsistency, the numerical difference between a reviewer's rating and the aggregate average for the product, the lower the perceived usefulness of the review. Finally, Qiu et al. (2012) looked at how conflicting aggregated ratings—discrepancies between an individual review's rating and the overall average—affected things. Their results show that such discrepancies harm the perceived credibility of the review and, therefore, the assessment of the product.

Understanding these elements helps marketers to know why a brand could be praised in official rankings but condemned in online forums (or vice versa). The digital landscape makes such contradictions more visible and frequent with universal user reviews and reputation scores.

1.4.2 How consumers resolve conflicting brand signals: insights from cognitive dissonance theory

Contradictory brand information can cause cognitive dissonance for consumers, the psychological discomfort of holding conflicting beliefs or evidence (Festinger, 1957). In the framework of my dissertation, this could happen, for instance, if a product marked "award-winning" provides a bad user experience. Cognitive Dissonance Theory (Festinger, 1957) posits that, much like hunger drives one to eat, this internal conflict is an unpleasant condition people want to lessen (Bran et Vaidas, 2020). Consumers confronted with conflicting brand signals will try to resolve or rationalize the conflict using several coping mechanisms. They might, for instance, look for more information to decide which source to trust, postpone their choice, or change their attitudes to bring back a feeling of consistency (Siddiqui et al., 2020). A recent study (2020) by University of South Florida researchers looking at how people respond when confronted with a set of conflicting top reviews found that consumers were 20% more likely to postpone their purchase decision and read more reviews if online reviews for a product were inconsistent, rather than commit to buying right away.

Consumers can also interpret the data differently or give it different weight to solve contradictory signals. Dissonance theory holds that people usually prefer information that fits their past beliefs or preferences (Festinger, 1957). A brand-loyal consumer might therefore minimize certain unfavorable reviews as anomalies or ascribe them to fussy or prejudiced critics, so preserving their good brand attitude. On the other hand, a doubtful customer might ignore the brand's claimed accolades or promises and focus more on the negative eWOM. In fact, studies have shown that conflicting heuristic cues (such as star ratings) and thorough attribute information together create attitudinal ambivalence, which then compromises purchase intentions until the conflict is resolved one way or another (Siddiqui et al., 2020). Consumers could try to reconcile the ambivalence by looking for alignment: for example, reading expert views to confirm user reviews (or the other way around) or searching for majority consensus to determine which signal to believe.

Psychologically, consumers can reconcile dissonance from contradictory brand signals via various mechanisms, including rationalization and selective information processing. Rationalization lets consumers internally justify differences, such as downplaying negative reviews in favor of salient positive signals like design awards, so creating a consistent story that lessens discomfort (Festinger, 1957; Ahmed et al., 2025). Consumers could also compartmentalize information, trusting a brand for certain qualities (e.g., quality signaled by awards or "most helpful" reviews) while remaining cautious about others (e.g., usability issues raised in user feedback), so modifying their expectations instead of rejecting either source directly (López-López & Parra, 2016). Petty & Cacioppo (1986), Chaiken (1980) and Ahmed et al. (2025) show how consumers handle conflicting information using both superficial cues (heuristics) and deeper reasoning (systematic or central route) in dual-process models like the Elaboration Likelihood Model (ELM) and the Heuristic–Systematic Model (HSM). For instance, in the realm of electronic word-of-mouth (eWOM), consumers might use the salience of a "most helpful" review as a heuristic indicator, particularly when it conflicts with the general review valence, which can greatly influence attitudes toward the salient review (López-López & Parra, 2016). Moreover, people who feel ambivalence or cognitive conflict are driven to look for information that confirms their current beliefs in order to alleviate discomfort—a process called selective exposure (Sawicki et al., 2013). Consumers with little problem knowledge show this tendency more since unknown pro-attitudinal information is seen as more powerful at lowering ambivalence (Sawicki et al., 2013). Psychological techniques therefore help consumers cope with the pain of cognitive dissonance and preserve internal consistency in their brand perceptions by means of rationalization, compartmentalization, and selective exposure, backed by dual-process theories (Festinger, 1957; Ahmed et al., 2025; Sawicki et al., 2013).

1.4.3 The impact on consumer's trust and loyalty

A consumer's inability to adjust conflicting signals in brand messages frequently results in a loss of trust and loyalty. As mentioned before, consumer trust in a brand is linked to the expectations of the brand's honesty, altruism, and dependability (Albert & Merunka, 2013). Maintaining a long-term relationship depends mostly on trust, which is also a prerequisite (Matzler et al., 2008; Morgan & Hunt, 1994). Thus, it may be viewed as confidence in the brand's performance (Albert & Merunka, 2013). Any utter discrepancy between the two can create uncertainty in a digital environment teeming with both brand-generated and user-generated content. In fact, a history of uneven brand experiences educates customers to be doubtful, therefore undermining the credibility of the next brand messages (Walter et al., 2024). According to cue-consistency theory, consistent cues boost information diagnosticity and more diagnostic cues increase purchase intention (Miyazaki, Grewal, & Goodstein, 2005; Purohit & Srivastava, 2001). Furthermore, consumers believe inconsistent reviews to be less useful and less trustworthy (e.g., Baek et al., 2012; Qiu, Pang, & Lim, 2012) since they postpone their product assessments (Afzal, Roland, & Al-Squri, 2009) and cause consumers to doubt the correctness of the product information, particularly when looking for an unobservable product quality (Akdeniz et al., 2013).

Equally significant is the effect on brand loyalty. Many academics looking at consumer-brand interactions (Bagozzi et al., 2017; Batra et al., 2012; Carroll & Ahuvia, 2006; Junaid et al., 2019;

Machado et al., 2019) have actually emphasized that brand trust is a major engine of brand loyalty. Positive, reinforcing experiences and communications drive brand loyalty; contrary signals create uncertainty that could compromise the emotional connection. Mixed reviews create attitudinal ambivalence, which has been proven to reduce consumers' desire to buy and recommend (Siddiqui et al., 2019).

Research indicates that people who suffer unresolved cognitive dissonance are more likely to create negative electronic word-of-mouth messages (He & So, 2022), participate in order cancellations and product returns (Bolia et al., 2021), and lower brand commitment and repurchase intentions (Sharifi et al., 2014). Furthermore, a study by Wilkins et al. (2018) indicated that cognitive dissonance could directly cause negative word-of-mouth behaviors, low loyalty, and consumer unhappiness. This cascade effect shows how psychological discomfort can be converted into observable behavioral effects harming brand equity. Finally, as Sharifi and Esfidani (2014) point out, post-purchase cognitive dissonance directly undermines satisfaction and loyalty, so its resolution is vital for preserving good consumer-brand interactions.

Unresolved dissonance can, over time, transform initial loyalty into indifference or perhaps aversion. In rare situations where customers believe a brand's conflicting signals have misled or betrayed them, they may act negatively by filing complaints, disseminating unfavorable word-of-mouth, or organizing boycotts (Zhigang et al., 2020). Most often, this occurs in the Corporate Social Responsibility setting. Wagner et al. (2009), for example, discovered that when a company's CSR assertions were discredited as meaningless (perceived hypocrisy), consumers formed very negative views and were more likely to punish the brand (Zhigang et al., 2020).

All things considered, contradictory brand perceptions can cause cognitive dissonance in consumers and motivate them to use different psychological tools to reconcile the paradoxes. Unresolved contradictions tend to erode the consumer-brand relationship: trust is compromised and loyalty is endangered.

Chapter 2: Understanding service quality and consumer perception in the airline industry

2.1 The airline industry: scale, structure, and importance

Few sectors influence our world as much as aviation. Without air travel, whole industries like leisure, tourism, and international business would be severely limited since the capacity to move fast across borders underlies both economic development and cultural exchange (Tiernan et al., 2008/1; Fly with Courage, 2023). Europe's skies recorded an incredible 10.7 million flights in 2024 alone, a number that almost matches pre-pandemic highs and highlights the continent's ongoing dependence on air connection (EUROCONTROL, 2024), as highlighted in Figure 6, where the evolution of the number of commercial flights in the EU throughout 2024 can be assessed.

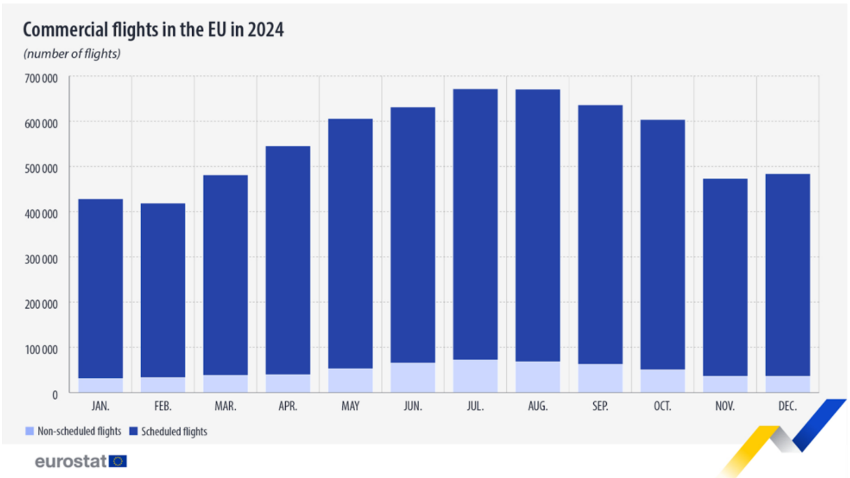


Figure 6: Number of commercial flights in the EU in 2024 by Eurostat

From the uncertainty of recent years, the airline sector worldwide has made a remarkable comeback. A record 9.5 billion people flew by air in 2024, surpassing pre-pandemic levels by 3.8%, and the sector made \$996 billion in income, with projections to exceed \$1 trillion in 2025 (IATA, 2024). Aviation now makes up 4.4% of world GDP and supports more than 87 million jobs, so it's one of the most important economic engines still running. This comeback is not only a matter of statistics (ATAG, 2024; IATA, 2024). Air travel also allows for the movement of 35% of the value of international trade, therefore reinforcing its contribution to world wealth (Fly with Courage, 2023).

The European airline industry, which this thesis will concentrate on, is both large and dynamic. The region's airlines took off more than 6.7 million commercial flights in 2024 and served more than 1.28 billion passengers, a 7% rise over the previous year and a complete recovery to pre-pandemic passenger levels (EUROCONTROL, 2024). While legacy carriers (e.g., Lufthansa) and regional airlines (e.g., Aeroitalia) adjust to changing demand and regulatory pressure, Low-Cost Carriers like

Ryanair, which alone ran almost 96,000 flights in 2024 and 2,771 in April 2025 alone, as shown in Figure 7, keep changing the industry (Statista, 2024).

#	AIRCRAFT OPERATOR	AVG. FLIGHTS	vs 2024	vs 2019
1	Ryanair Group	2.771	+7%	+34%
2	Turkish Airlines Group	1.394	+3%	+11%
3	easyJet Group	1.390	+7%	-9%
4	Lufthansa Airlines	1.037	-1%	-28%
5	Air France Group	966	+9%	-17%
6	KLM Group	829	+3%	+6%
7	Wizz Air Group	820	+6%	+62%
8	British Airways Group	809	+2%	-8%
9	SAS Group	625	+11%	-20%
10	Vueling	563	+4%	+9%

Figure 7: Average Daily Flights by Aircraft Operator in Europe (April 2025) by EUROCONTROL

Still, the size of the sector causes complexity. Air travel, one of the most intangible services (Kloppenborg & Gourdin, 1992; Shostack, 1977), has emerged as a significant challenge as competition requires high-quality, delightful experiences (Dennett et al., 2000). According to research, when prices and frequent flyer programs are similar, travelers regularly prefer airlines with better perceived service quality (Ostrowski et al., 1993). In a sector characterized by high operational costs, regulatory complexity, and external shocks like fluctuating fuel prices and geopolitical instability, this emphasis on satisfaction is not only strategic but also crucial for survival (Lufthansa Group, 2024). European airlines are projected to make a net profit of $9 billion (3.8% margin) in 2024, but this profitability is concentrated among a few major groups-such as IAG, Air France-KLM, Lufthansa Group, and Ryanair - while many smaller carriers struggle with continuous consolidation and fierce competition (IATA, 2024). The European market still stands out for its creativity and flexibility. To satisfy rigorous EU safety and environmental criteria, top carriers are spending money on fleet modernization, sustainable aviation fuels, and improved passenger experiences.

2.1.2 Segmentation: Full-Service vs Low-Cost Carriers

Fundamentally, the airline sector can be divided by core activity into passenger airlines and freight airlines (Airline Business Models, 2008). Because this thesis focuses on passenger dissatisfaction with commercial airlines, the subsequent debate will center on the categorization and differentiation of passenger airlines, which is critical for understanding how service quality and satisfaction are delivered and perceived.

A classic framework for airline segmentation is based on differentiation strategy: price versus service (Jones & Sasser, 1995). This distinction is most evident in the contrast between Full-Service Network Carriers (FSCs), often referred to as legacy airlines, and Low-Cost Carriers (LCCs). In Table 1 below, the key differences between the two types of airlines have been summarized for an easy comparison.

Features	Low-Cost Carriers (LCCs)	Full-Service Carriers (FSCs)
In-flight Services	No frills (pay-per-service)	Complimentary meals, entertainment, checked luggage
Network Structure	Point-to-point	Hub-and-spoke
Airport Type	Secondary	Primary
Fleet	Standardized, one aircraft type	Diverse, multiple aircraft types
Turnaround Times	Short (maximize aircraft use)	Longer (operational complexity)
Travel Classes	Single class	Multiple classes: economy, business, first
Loyalty Programs	Generally absent (evolving)	Frequent flyer program
Alliances	Non-affiliated or independent	Global alliances (e.g., Star Alliance)
Target Customers	Price- and time-sensitive travelers	Business and leisure travelers
Pricing Strategy	Price differentiation: base fare + extras	Service differentiation
Booking Channels	Internet, direct	Internet, direct, travel agents
Service Quality	Basic but often efficient (e.g., punctuality)	Comprehensive, but sometimes less efficient
Recent Innovations	Offering premium services or loyalty programs	Adopting low-cost elements on short-haul routes
Expansion and Connectivity	Limited, focused on short/regional routes	Extensive, includes long-haul intercontinental flights
Examples	Ryanair, easyJet, Wizz Air	Lufthansa, Air France-KLM, British Airways

Table 1: Key differences Between Low-Cost Carriers and Full-Service Network Carriers, adapted from Adapted from Holloway (2008) and O'Connell & Williams (2005)

Characterized by a thorough service offering including several cabin classes, frequent flyer programs, and a hub-and-spoke network structure centered on major airports, Full-Service Network Carriers (FSCs) are usually part of worldwide alliances like Star Alliance. These airlines, like Lufthansa, Air France-KLM, and British Airways, seek to expand their network reach and offer smooth international connectivity (IATA, 2024). Their business model is based on service differentiation: they target both business and leisure travelers, offer a broad range of routes (including long-haul intercontinental flights), and provide amenities such as complimentary meals, checked baggage, and in-flight entertainment (Combe, 2023; Chopra & Lisiak, 2006; ReadyForTakeoff, 2024). Further segmentation within the FSCs category exists depending on travel class - economy, business, or first - with some airlines like Emirates and Qatar Airways providing luxury services such as onboard spas and private suites.

By reducing operational costs and providing basic, no-frills service, Low-Cost Carriers (LCCs), on the other hand, emphasize price differentiation (Tiernan et al., 2008/1; Liou & Tzang, 2007). Operating point-to-point routes, usually from secondary airports, airlines like Ryanair, easyJet, and Wizz Air maximize aircraft use by fast turnaround times and a standardized fleet (Chopra & Lisiak, 2006; ReadyForTakeoff, 2024). Unbundling shapes the LCCs model: the base fare covers just the seat; extra costs apply for other services, including seat selection, checked luggage, and onboard food (CORE, 2007). With the cost of flying down by almost 75% since the 1950s (IATA, 2024), this strategy lets LCCs attract very price-sensitive consumers and has helped to significantly democratize air travel in Europe. Interestingly, recent studies indicate that LCCs occasionally outperform legacy carriers in particular service quality criteria, especially on-time performance and operational efficiency (Liou & Tzang, 2007; Academia.edu, 2022). Although these two models are different, the lines are getting more and more foggy. While LCCs have started to provide premium services or loyalty programs to grab more market sectors, some FSCs have incorporated aspects of the low-cost model on short-haul routes (IATA, 2024; Combe, 2023).

Service quality is still the foundation of airline competitiveness and customer retention regardless of business model (Gursoy et al., 2005; Chang & Yeh, 2002; Dennett et al., 2000). Airlines have to constantly change their service offerings to fit different and changing passenger expectations since the main product of the sector is an intangible experience (AviationFile, 2025; IJFMR, 2024). Good service quality not only fosters loyalty and repeat business but also lowers crisis management expenses and operational inefficiencies (AviationFile, 2025; APEX, 2024).

2.2 Service Quality and Passenger Satisfaction in Airlines

2.2.1 Defining Service Quality in the Airline Sector

In the context of the airline industry, service quality has long been recognized as a critical factor for competitiveness, customer retention, and profitability (Lewis, 1989; Edvardsson, 1992). Service quality is typically defined as "the extent to which a service meets or exceeds customer expectations" (Parasuraman, Zeithaml, & Berry, 1985, 1988; Grönroos, 1982), encompassing both technical outcomes (what is delivered) and functional quality (how it is delivered) (Grönroos, 1984). In airlines, this duality often appears as a distinction between ground services (ticketing, check-in, baggage) and in-flight services (crew interaction, meals, comfort) (Chen & Chang, 2005; Park, 2007).

The **SERVQUAL model** (Figure 8), developed by Parasuraman et al. (1988), remains the most widely used tool to assess perceived service quality, measuring five key dimensions:

1. Tangibles (physical facilities and appearance)
2. Reliability (ability to perform promised service dependably)
3. Responsiveness (willingness to help and provide prompt service)
4. Assurance (knowledge and courtesy of employees, ability to inspire trust)
5. Empathy (caring, individualized attention).

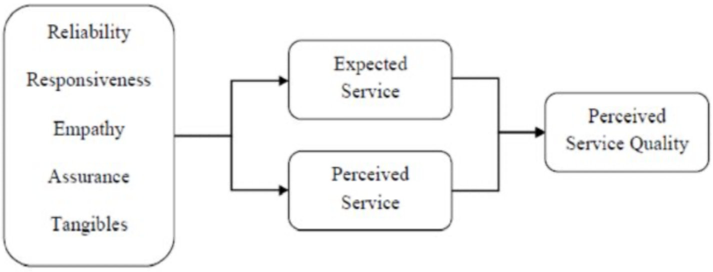


Figure 8: SERVQUAL model (Parasuraman et al., 1988)

Building on this model, Fitzsimmons and Fitzsimmons (2001) explain that service quality is shaped by the interaction between two key components: **expected service** (what the customer anticipates before the service encounter) and **perceived service** (what the customer actually experiences). As shown in Figure 9, expectations are influenced by factors such as word of mouth (which we will later discuss in 2.3), personal needs, and past experiences, while perceived service is evaluated through key service quality dimensions like reliability, responsiveness, assurance, empathy, and tangibles (Parasuraman et al., 1988). The perceived service quality ultimately emerges from comparing these two elements.

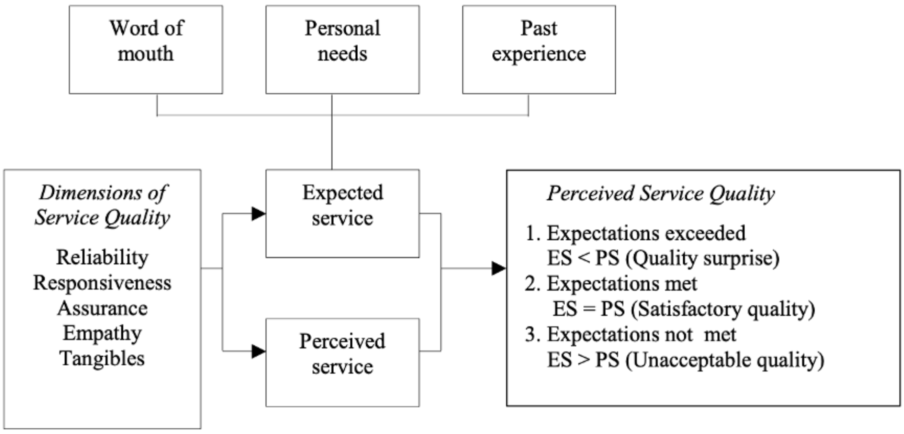


Figure 9 : Perceived service quality model (Fitzsimmons & Fitzsimmons, 2001)

This framework clearly highlights the tight connection between **service quality and customer satisfaction**: customers form satisfaction judgments based on whether the service performance meets, exceeds, or fails to meet their prior expectations. Indeed, to achieve a high level of customer satisfaction, most researchers suggest that a high level of service quality should be delivered by the service provider, as service quality is normally considered an antecedent of customer satisfaction (Cronin, Brady, and Hult, 2000; Anderson et al., 1994; Cronin and Taylor, 1992).

However, recognizing the unique context of air transport, several scholars have proposed sector-specific adaptations. For example, Nadiri et al. (2008) developed the **AIRQUAL scale**, which integrates aspects like airline image and terminal tangibles, while Wu and Cheng (2013) proposed a hierarchical model that captures interactions, physical environment, outcomes, and access. Such adaptations reflect the complexity of airline service delivery, where physical infrastructure, operational efficiency, and interpersonal interaction combine to shape customer perceptions (Liou et al., 2011; Han & Hyun, 2017).

Another configuration is the **Grönroos Model** (Grönroos, 1984), which offers a foundational conceptualization of service quality by distinguishing between two key dimensions: technical quality and functional quality, as emphasized in Figure 10. Technical quality refers to what the customer receives, that is, the core outcome or technical result of the service (for airlines, this might be the successful and safe transportation of passengers to their destination). Functional quality, on the other hand, refers to how the service is delivered, the manner and process by which the customer experiences the service, such as the courtesy, responsiveness, and professionalism of the airline staff. Grönroos argues that while both dimensions matter, functional quality often has a stronger impact on customer perceptions because it is more visible and subjectively experienced by the customer during service encounters. Additionally, Grönroos incorporates the idea of corporate image, suggesting that customer perceptions are shaped not only by direct service encounters but also by the overall reputation and brand image of the airline.

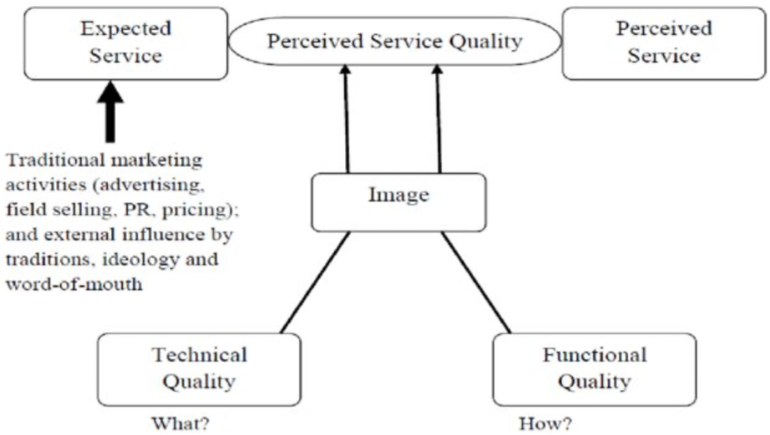


Figure 10: The Gronroos model (Gronroos, 1984)

Beyond Grönroos, several researchers have proposed models that break down service quality into more attribute-specific components, particularly tailored to the airline industry. These models typically group quality into three broad categories:

1. **Performance-related attributes** — These include measurable operational factors such as punctuality (on-time departures and arrivals), safety records, and baggage handling accuracy

(Gourdin, 1988; Elliott & Roach, 1993). These attributes directly reflect the airline's ability to deliver its core promise reliably and efficiently.

2. **Service-related attributes** — These refer to the quality of the interactions between passengers and airline staff, including courtesy, friendliness, professionalism, and responsiveness (Gilbert & Wong, 2003; Pakdil & Aydın, 2007). These factors contribute significantly to passengers' emotional and psychological experience, particularly during service recovery situations or when assistance is needed.
3. **Basic product attributes** — These encompass the fundamental physical and logistical elements of the flight experience, such as seat comfort, legroom, cabin cleanliness, in-flight meals, entertainment, and flight schedule convenience (Lim & Tkaczynski, 2017; Brochado et al., 2019).

All in all, to provide a unified perspective, Table 2 below summarizes the various models that have been used to measure service quality.

Study/Model	Key Attributes/Domains
Parasuraman et al. (1988)	Tangibles, Reliability, Responsiveness, Assurance, Empathy
Tsaur et al. (2002)	Crew language skills, seat comfort, food, ticketing, crew professionalism, timeliness, safety
Gilbert & Wong (2003)	Knowledge, safety, employee behavior, baggage handling, prompt service, clean seats, in-flight entertainment
Park et al. (2004)	Aircraft/facility, personal attention, meal, seating, check-in, safety record, in-flight entertainment
Nadiri et al. (2008)	Airline tangibles, terminal tangibles, personnel, empathy, image (AIRQUAL)
Bowen et al. (1992)	On-time performance, mishandled baggage, oversales, customer complaints, safety, comfort, price
Brochado et al. (2019)	Ground and in-flight services, staff, seat comfort, entertainment, overall experience

Table 2: Literature summary of key service quality attributes used in the airline sector (own elaboration)

Despite these advancements, accurately measuring service quality in airlines remains challenging due to the intangible, heterogeneous, and perishable nature of services (Tiernan et al., 2008). Recent scholarship emphasizes the importance of blending quantitative indicators (e.g., on-time performance, baggage handling) with qualitative dimensions (e.g., staff courtesy, comfort) to achieve a holistic understanding of service performance (Bowen, Headley, & Luedtke, 1992; Park et al., 2020).

2.2.2 Relationship between service quality and customer satisfaction

The relationship between service quality and passenger satisfaction has been extensively studied in airline marketing and service research. A substantial body of work has explored how service quality relates to customer satisfaction and loyalty within the airline industry (Ostrowski et al., 1993; Curry & Gao, 2012; Chen & Hu, 2013; Namukasa, 2013; Chow, 2014, 2015). Numerous studies have consistently confirmed that service quality acts as a key antecedent to customer satisfaction in this context (Saha & Theingi, 2009; Archana & Subha, 2012; Leong et al., 2015; Hussain, 2016), showing that as passengers' perceptions of service quality increase, so does their satisfaction (Lau et al., 2011). Furthermore, prior research suggests that passenger satisfaction is a crucial driver of behavioral intentions, influencing outcomes such as loyalty, repurchase intentions, and positive word-of-mouth (Park et al., 2004, 2006; Clemes et al., 2008; Nadiri et al., 2008; Saha & Theingi, 2009; Leong et al., 2015; Singh, 2015; Hussain, 2016; Liu & Lee, 2016). Both business and leisure travelers value high service quality, underscoring its importance in meeting the expectations of diverse customer segments (Young et al., 1994).

Conceptually, customer satisfaction has been delineated in many ways. According to Bowen et al. (1992) passenger satisfaction, in its simplest form, can be defined as airline service quality. In other words, quality is continuously satisfying customer requirements (Smith, 1987). In the airline industry, passenger satisfaction is reflected in airline and government statistical reports by on-time performance, mishandled baggage, oversales, and consumer complaints (Bowen et al., 1992). More recently, Yao et al. (2019) have described it as an experience made on the basis of a specific service encounter, and it contributes to customer loyalty, repeat purchases, favorable word-of-mouth (WOM), and ultimately higher profitability. Essentially, satisfaction is often framed as the result of perceived service quality, following models such as the service-profit chain (Heskett et al., 1994) and the expectancy-disconfirmation paradigm (Oliver, 1980). When passengers perceive that an airline's service quality exceeds their expectations, they experience satisfaction; when perceptions fall short, dissatisfaction arises.

Numerous empirical studies confirm the strong, positive relationship between service quality and satisfaction in the airline industry. Cronin and Taylor (1992) demonstrated that service quality has a direct impact, and it is an antecedent of customer satisfaction, which in turn drives behavioral intentions such as repurchase and recommendation. Saha and Theingi (2009) extended this model in the aviation context, showing that perceived service quality significantly predicts both satisfaction and loyalty. Similarly, Pakdil and Aydın (2007) found that responsiveness, reliability, and assurance are the most important quality dimensions affecting Turkish airline passengers' satisfaction, while Gilbert and Wong (2003) highlighted the central role of staff empathy and responsiveness in shaping satisfaction among Asian airline travelers.

Interestingly, the relationship between service quality and satisfaction is not symmetrical. Research shows that negative experiences, or service failures, often have a disproportionately strong effect on dissatisfaction compared to the positive effect of good service on satisfaction (Namukasa, 2013). While many studies emphasize the importance of enhancing service quality to increase satisfaction and loyalty (Parasuraman et al., 1988; Ostrowski et al., 1993; Park et al., 2004; Brochado et al., 2019), recent research highlights that the absence or poor execution of certain fundamental service attributes, such as punctuality, efficient baggage handling, and smooth Check-in Processes can generate strong dissatisfaction, even when other aspects of the service meet or exceed expectations (Park, Lee & Nicolau, 2020; Liau & Tan, 2014; TNMT, 2024). Operational disruptions such as flight delays, cancellations, lost luggage, and inefficient boarding consistently emerge as the leading sources of passenger frustration, as clearly underlined in Figure 11, often overshadowing improvements in areas like food quality or in-flight entertainment (TNMT, 2024; Liau & Tan, 2014).

The persistent gap between customer expectations and actual experiences, exacerbated by industry-wide challenges such as staff shortages and increased travel demand, has only deepened traveler frustration in recent years (TNMT, 2024). Addressing these dissatisfiers is therefore essential not only for improving satisfaction scores but also for sustaining customer loyalty and generating positive word-of-mouth in a highly competitive market (Brochado et al., 2019).

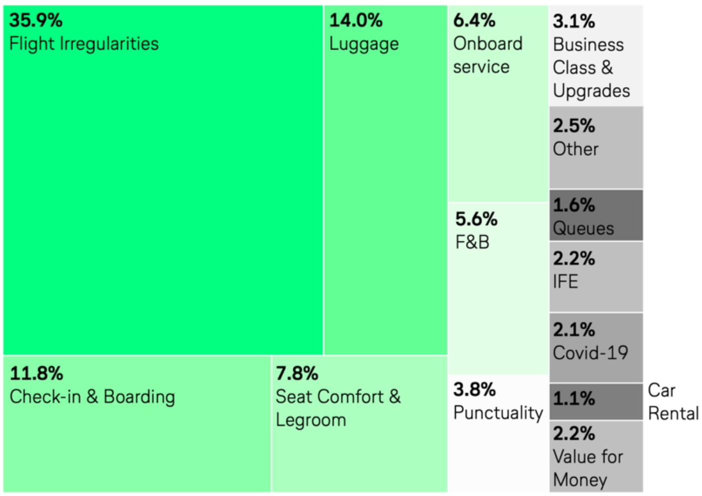


Figure 11: Distribution of airlines review topics on Tripadvisor by TNMT

To quickly recap key studies identifying both the drivers of satisfaction and the main dissatisfiers reported in the airline literature, Table 3 below summarizes them, presenting an overview of what airlines should prioritize, not just to create satisfied passengers, but to prevent dissatisfaction from taking hold.

Author(s)	Key Satisfaction Drivers	Key Dissatisfiers
Parasuraman et al. (1988); Grönroos (1984)	Functional quality (staff courtesy, empathy); technical quality (safe delivery, operational efficiency)	Failures in functional or technical aspects (delays, poor interactions)
Ostrowski et al. (1993)	Overall service quality consistency; meeting expectations across multiple trips	Inconsistency in service performance across routes or time
Bowen et al. (1992)	On-time performance, low complaint rates, baggage handling	Delays, overbooking, mishandled baggage
Cronin & Taylor (1992)	Perceived service quality, responsiveness, assurance	Slow service recovery, unmet expectations
Saha & Theingi (2009)	Service reliability, staff professionalism, airline image	Poor communication during service failures, perceived unfairness
Pakdil & Aydın (2007)	Responsiveness, reliability, assurance	Lack of proactive assistance, unresolved passenger concerns
Gilbert & Wong (2003)	Staff empathy, responsiveness, personalized service	Rude or inattentive staff, lack of empathy
Namukasa (2013)	Value for money, convenience, good service delivery	Service failures (delays, cancellations), ineffective problem resolution
Park et al. (2004, 2006)	Consistent service experience, frequent flyer benefits, staff courtesy	Inconsistent handling of loyalty customers, lack of tangible rewards
Leong et al. (2015)	Reliability, assurance, tangible service features	Lack of reliability, broken service promises
Hussain (2016)	Service quality leading to loyalty, positive behavioral intentions	Low service quality damaging loyalty, leading to negative behavioral responses
Lau et al. (2011)	High perceived quality directly increasing satisfaction	Low perceived quality amplifying dissatisfaction
Yao et al. (2019)	Positive service encounters enhancing loyalty, repeat purchases, and WOM	Negative service encounters harming loyalty and triggering negative WOM
Brochado et al. (2019)	In-flight comfort, entertainment, staff professionalism	Physical discomfort, inadequate entertainment, impolite staff
Ban & Kim (2019)	Positive e-WOM reinforcing satisfaction, shaping expectations	Negative e-WOM amplifying dissatisfaction and damaging brand perception

Table 3: Summary of key satisfaction and dissatisfaction drivers, based on a review of academic literature (own elaboration)

In summary, the relationship between service quality and satisfaction in the airline sector is both well-established and multidimensional. Airlines that deliver consistent, high-quality service across both functional and emotional dimensions are more likely to satisfy their customers, retain loyalty, and generate positive word-of-mouth, which in turn sustains long-term competitive advantage (Liou et al., 2011; Rajaguru, 2016).

2.3 The Role of e-WOM and Online Reviews in the Airline Industry

The growing influence of word-of-mouth (WOM) communication, particularly in its electronic form (eWOM), on consumer behavior, brand perception, and purchasing decisions is something that the modern airline industry should definitely focus on. With the introduction of digital platforms, passengers now play an active role in shaping the public image of airline services. Recent research on consumer behavior shows that approximately 71% of travelers base their booking decisions on digital WOM and peer reviews, while 88% consider online reviews when selecting an airline (YouGov, 2023).

This transformation in how airline services are evaluated and recommended has gained increasing academic attention. Nikookar et al. (2015) demonstrated that WOM significantly influences consumers' attitudes and referral intentions, identifying its antecedent in satisfaction, loyalty, perceived value, service quality, and trust. Building on this, Kim and Park (2017) found that online WOM indirectly affects behavioral intentions through customer satisfaction, stressing its mediating role in the decision-making process.

Along with the growth of digital engagement, scholars began to focus on the impact of social media and review platforms in amplifying WOM. Traditional service quality metrics, such as the Airline Quality Rating (AQR), though objective, often fail to capture customer perception, which many scholars argue plays a more influential role in consumer evaluation (Park et al., 2007; Blackwell, Miniard, & Engel, 2006). In contrast, user-generated content (UGC), including online reviews and feedback on platforms such as TripAdvisor, Skytrax, and Twitter, offers a more dynamic and accurate reflection of customer experiences. UGC provides the advantages of real-time feedback, broader audience reach, and reduced biases inherent in conventional surveys (Cheung & Thadani, 2012; Forman, Ghose, & Wiesenfeld, 2008; Kamins & Assael, 1987). Moreover, a survey has been conducted by YouGov (2023) to explore demographic and geographic variations in eWOM reliance. The results of the poll indicate that younger consumers aged 25–44 are significantly more likely to rely on eWOM when choosing airlines, while older generations express more skepticism. Regional patterns also show that consumers in Asian markets such as the UAE, Hong Kong, Indonesia, and India are more influenced by eWOM compared to those in Scandinavian countries like Sweden and Denmark. These findings underscore the strategic need for airlines to monitor and manage their digital reputation across diverse markets.

Expanding on the decision-making perspective, Lerrthaitrakul and Panjakajornsak (2014) developed a conceptual framework to analyze how eWOM affects consumer buying behavior in the low-cost airline industry. Their model, visualized in Figure 12, identifies three key eWOM variables—information credibility, volume, and online opinions—and explains their influence across three stages of the consumer journey: pre-purchase, purchase, and post-purchase.

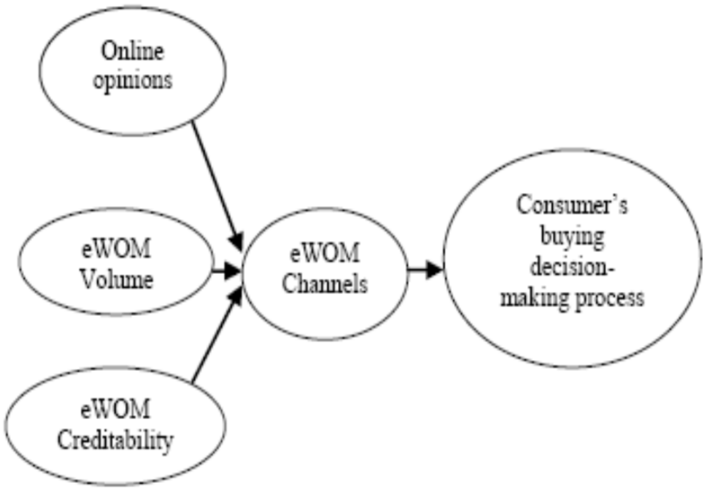


Figure 12: Conceptual model of eWOM influence in the low-cost airline sector (Lertthaitrakul & Panjakajornsak, 2014)

Their study found that credible and high-volume eWOM significantly shaped consumer decisions, particularly through social media and online review platforms. Importantly, eWOM engagement was shown to continue after the purchase, creating a feedback loop that impacts future consumer behavior. The authors conclude that managing eWOM is essential for enhancing service perception and customer engagement in the low-cost airline segment (Lertthaitrakul et Panjakajornsak, 2014).

Yodpram and Intalar (2020) further examined the effect of eWOM on consumer willingness to pay more (WTP) for low-cost airline services. They found that eWOM significantly enhances brand image, which in turn influences both brand attitude and WTPM. However, eWOM did not directly affect WTPM; instead, the effect was fully mediated by brand-related constructs. These results suggest that a strong digital presence and reputation can justify premium pricing when channeled through positive brand perception (Elseidi & El-Baz, 2016; Pratiwi & Yasa, 2019). Complementing these insights, Ahmad, Abuhashesh, Obeidat, and AlKhatiba (2020) explored the influence of eWOM on consumers' intentions to purchase airline e-tickets. Their findings confirm that eWOM has a direct and significant impact on online purchasing decisions, a relationship further mediated by online trust. Dimensions such as source credibility, expertise, trustworthiness, and the volume and quality of e-WOM were all found to be critical.

Finally, Quan, Khoa, and Nguyen (2023) expanded the discussion to include airport service quality and its role in driving eWOM. Using the Stimulus-Organism-Response (S-O-R) framework, they found that service quality dimensions, like check-in, ambiance, mobility, and others, significantly influence passenger satisfaction, which in turn strongly predicts eWOM behavior. Among these, check-in services had the most substantial impact on satisfaction. Their findings align with earlier literature (Akamavi et al., 2015; Koklic et al., 2017) and emphasize the importance of operational excellence in fostering digital word-of-mouth.

Considered all together, these studies illustrate the evolving landscape of consumer decision-making in the airline sector, determined by the interaction of service quality, customer satisfaction, and electronic word-of-mouth. The literature suggests that airlines and airports must not only deliver superior service experiences but also strategically engage with customers in the digital space to enhance loyalty, influence purchasing decisions, and maintain a competitive edge.

2.4 Case studies: applications of review analysis in the airline sector

Online consumer reviews have become an essential resource for customers to assess the strengths and weaknesses of products and services prior to making purchasing decisions since the sentiment expressed in reviews significantly affects their perceived helpfulness (Salehan & Kim, 2016). In the air transport industry, where—as in any other service sector - service quality directly impacts customer satisfaction (Hesskett et al., 1994), reviews provide valuable, unsolicited feedback that can inform both operational and strategic decisions. Consequently, the systematic analysis of online consumer reviews can offer a vigorous opportunity for airlines to measure and improve passenger satisfaction almost in real time (Saha & Theingi, 2009).

In this upcoming section, I am going to present three case studies that I think best illustrate how online consumer reviews can be leveraged to assess and interpret airline service quality using various data sources and analytical methods. Each case study was selected to highlight a unique combination of data origin, analytical focus, and airline classification, thereby offering a comprehensive view of the intersection between online reviews and service evaluation. The first case study is based on Skytrax, a global platform specializing in airline reviews, and employs text mining techniques to explore cross-regional variations in passenger expectations and satisfaction. The second case study focuses on Twitter data, where real-time micro-reviews are used to assess brand perception and sentiment through social media analysis. The final case study uses a structured American airport survey dataset to implement data mining and machine learning methods, offering insights into satisfaction patterns within full-service airlines. Together, they provide a comparative framework that not only demonstrates the versatility of text and data mining techniques, which will be discussed later, but also shows how online customer reviews vary depending on the context, be it the type of platform, the nature of the dataset, or the class of airline under review.

2.4.1 Case study 1: text mining analysis of Skytrax reviews to uncover regional variations in airline passenger expectations

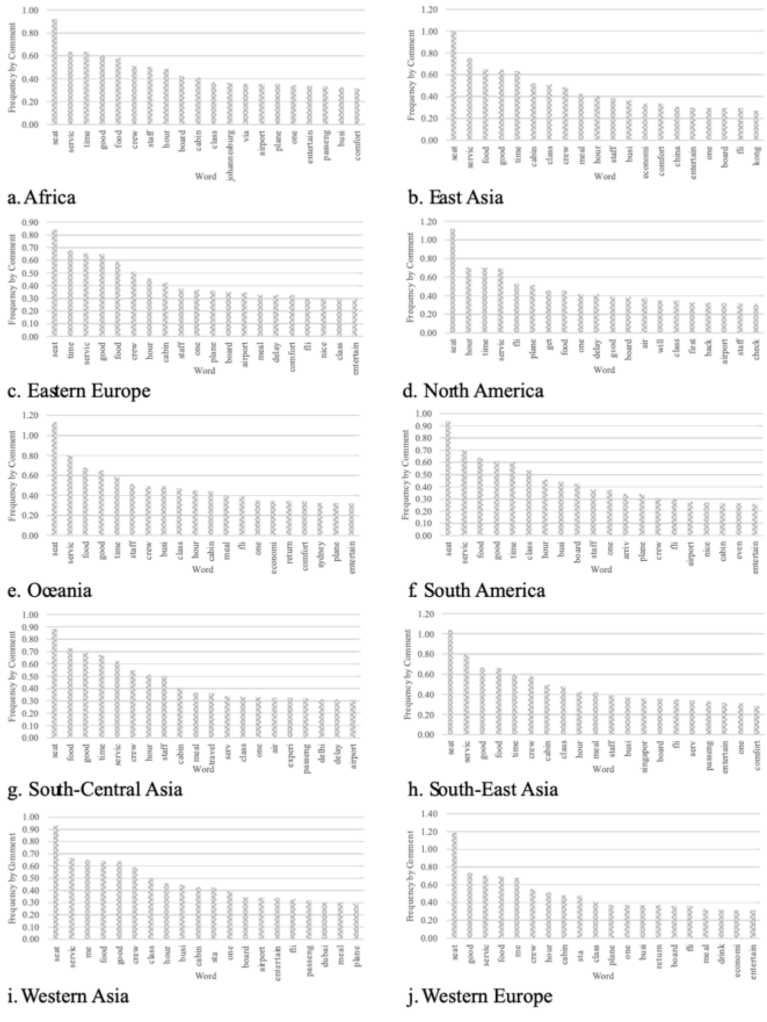
Skytrax is a consultancy firm located in London which does advisory research mainly within the air transport sector (Izenman, 2008). On an annual basis, this company carries out surveys to update the star-based global Airlines Rating program (1-5) and present related awards (Yakut et al., 2015), such as "World Airline Awards" and "World Airport Awards" (Wikipedia, 2011a). This program has attracted international interest and has been adopted by some airlines for promotional purposes (Pérezgonzález & Gilbey, 2011). This platform is usually recognized as the largest airline review site worldwide, with over 670 airlines opened for review and millions of airlines and airports reviews (Pérezgonzález & Gilbey, 2011). However, according to Jacsó (2009), this program also bears controversies. Firstly, it includes a relatively small number of airlines compared with the total number of airlines that were open to review, lacking representativeness of the whole industry. Moreover, almost half the number of airlines are grouped into the 3-Star Airlines, leading to this type of airlines being unable to differentiate each other. Further, this program compares Low-Cost Carriers together with regular incumbents. This configuration can be confusing since these two types of airlines do not share too many similarities concerning the service standard. Given the extensive body of literature done on Skytrax, I have chosen to summarize the key contributions and findings in Table 4 below.

Author (s)	Year	Title	Main findings
Murugesan, S., et al.	2024	Forecasting Airline Passengers' Satisfaction Based on Machine Learning Using Skytrax Airline Reviews	Identified seat comfort, cabin crew service, and value for money as the top predictors of passenger satisfaction. Their machine learning models achieved 85% accuracy in predicting overall satisfaction.
Syed, A. N., et al.	2024	Airline Reviews Processing: Abstractive Summarization and Rating-Based Sentiment Classification Using Deep Transfer Learning	Found discrepancies between Skytrax star ratings and textual sentiment in 18% of cases. Their BERT model achieved 91% accuracy in sentiment classification from review text.
Jindal, S., et al.	2024	Airline Customer Satisfaction Prediction Using Machine Learning	Identified digital experience (e.g., mobile check-in) and ground service efficiency as emerging critical factors post-pandemic. Their Extra Trees Classifier achieved 99.87% accuracy in predicting satisfaction.
Li, X.	2023	Assessing the Reliability and Validity of the Global Airlines Rating Program	Skytrax ratings showed only 62% correlationwith actual passenger sentiment. The study revealed that reviews from 5-star airlines contained uncommonly negative outliers, indicating potential reliability issues.
Tri Noviantoro & Jen-Peng Huang	2022	Investigating Airline Passenger Satisfaction: Data Mining Method	Using Twitter data, they found that baggage handling, online/mobile boarding, and in-flight Wi-Fi/entertainment are the most critical drivers of satisfaction.
Kritya & Walanchalee	2021	Data Analytics of Skytrax's Airport Review and Ratings	Business travelers rate airports 23% more critically than leisure travelers on Skytrax. Terminal comfort had the highest impact on overall ratings.
Song, C., Guo, J., Zhuang, J.	2020	Analyzing passengers' emotions following flight delays: a 2011-2019 case study on Skytrax comments	Found significant negative correlationbetween passenger emotions and flight delay experiences. After delays, passenger attention to service aspects increased while airport service satisfaction dropped dramatically.
Punel, A., Al Hajj Hassan, L., Ermagun, A.	2019	Variations in airline passenger expectation of service quality across the globe	North American passengers complained more about national airlines and prioritized value for money. East Asian passengers were more satisfied with Asian airlines and placed higher importance on in-flight services.
Adeniran, A., Fadare, S. O.	2018	Relationship between passengers' satisfaction and service quality in Murtala Muhammed international airport, Lagos, Nigeria	Found significant correlation between airport service quality variables and passenger satisfaction. Staff courtesy and security screening were the strongest predictors of overall satisfaction.
Jeong, E. Y.	2017	Analyze of airlines online-reviews: Focusing on Skytrax	Discovered that negative reviews focused mainly on service recovery failures rather than initial service failures. Non-Asian carriers received more criticism for staff attitude than Asian carriers.
Liau, B. Y., Tan, P. P.	2014	Gaining customer knowledge in low cost airlines through text mining	Reported that text mining contributed to improvements in airlines' brand awareness, loyalty and recognition. Moreover, more positive was more present than negative sentiment in low-cost carrier reviews.
Yayla-Kullu, H. M., Tansitpong, P.	2013	A critical evaluation of US airlines' service quality performance: Lower costs compared to satisfied customers	Revealed that low-cost carriers can match or exceed full-service carriers in customer satisfaction despite lower operating costs. In-flight service quality had the greatest impact on overall satisfaction.
Pérezgonzález, J. D., Gilbey, A.	2011	Predicting Skytrax airport rankings from customer reviews	Demonstrated that text reviews could predict Skytrax star ratings with 76% accuracy. The strongest predictors were references to terminal cleanliness and immigration processing speed.
Lohmann, G., et al.	2009	From hub to tourist destination-An explorative study of Singapore and Dubai's aviation-based transformation	Identified how Singapore and Dubai leveraged airport development strategies to transform from transit hubs to tourist destinations, with customer experience as a key factor.
Mason, K. J., Morrison, W. G.	2008	Towards a means of consistently comparing airline business models with an application to the 'low cost' airline sector	Developed a comparative framework for airline business models using Skytrax data, finding that service quality ratings correlated with profitability regardless of business model.
Park, J. W., Robertson, R., Wu, C. L.	2006	The effects of individual dimensions of airline service quality: Findings from Australian domestic air passengers	Identified that in-flight service and reliability were the most significant predictors of Australian passenger satisfaction, with customer value mediating the relationship between service quality and satisfaction.
Gillen, D., Lall, A.	2004	Competitive advantage of low-cost carriers: Some implications for airports	Found that airports serving low-cost carriers received consistently different service quality ratings, particularly in ground transportation and terminal amenities.

Table 4: Summary view of the main academic studies done on Skytrax (own elaboration)

Out of all of these studies, I am going to analyze only the paper by Punel, Al Hajj Hassan, and Ermagun (2019) titled "Variations in Airline Passenger Expectation of Service Quality Across the Globe," published in *Tourism Management*, to gain a piece of understanding of how cultural and regional factors shape customer perceptions in aviation services.

The study draws on a notable dataset of more than forty thousand passenger reviews from the Skytrax platform, spanning from October 2011 to January 2018, encompassing 161 countries. The authors segment this data into ten geographical regions, including Africa, East Asia, North America, and Western Europe, and further differentiate between economy and first/business class passengers. Through this multidimensional lens, the paper investigates three primary hypotheses: (1) flight service characteristics have direct and indirect impacts on overall flight experience; (2) passenger expectations differ by geographical region; and (3) passenger expectations differ between flight classes. A central strength of this paper lies in its innovative methodological approach. Indeed, the authors decided to employ a mixed-methods analytical framework that integrates text mining techniques, sentiment analysis, and path analysis. Text mining is used to extract meaningful patterns from the qualitative review data, identifying the most frequently mentioned words in passenger reviews across ten major global regions, to uncover the specific aspects of the flight experience that passengers from different regions prioritize. For example, the word "seat" was found to be the most frequently used term in all regions, underscoring the universal importance of seat comfort, as shown in Graph 1 below.



Graph 1: Average frequency of top 20 review words across regions (Punel et al.2019)

To further explore the tone and emotional content of the reviews, they then applied sentiment analysis using a lexicon-based approach. This involves calculating a sentiment score for each review by assessing the balance of positive and negative words, thus capturing the overall sentiment or attitude expressed by the passengers. Lastly, the core quantitative component is the path analysis to examine both the direct and indirect effects of several service characteristics on overall flight satisfaction and perceived value for money. This method enables the researchers to test their hypotheses regarding the influence of cabin class and geographical background on passenger expectations.

Key findings highlight marked regional differences in passenger expectations. North American passengers, for example, are predominantly price-sensitive and less attentive to in-flight services, with a notable tendency to rate local airlines more harshly. In contrast, East and Southeast Asian passengers place strong emphasis on service quality, particularly regarding in-flight services and seat comfort. Across all regions, seat comfort consistently emerged as the most crucial factor influencing perceptions of value for money, whereas cabin staff service was most influential in shaping overall flight experience. The study also uncovers class-specific distinctions. First and business class passengers exhibited heightened concern for comfort, food quality, and entertainment, whereas economy passengers were more focused on price-performance balance. This differentiation suggests the importance of tailored service strategies for different market segments, reinforcing the notion that "one size fits all" approaches are ineffective in the competitive airline sector.

The paper contributes significantly to the literature by filling a gap on cross-cultural comparisons in airline service expectations, a topic previously underexplored despite its practical relevance. It is placed into a broader discourse on the role of electronic word-of-mouth (eWOM) in shaping consumer behavior, noting that platforms like Skytrax function both as marketing tools and rich data sources for service evaluation.

2.4.2 Case study 2: real-time sentiment and brand perception on airline reviews on Twitter

Moving on to another user-generated content platform - Twitter - the second case study, *"Gaining Customer Knowledge in Low-Cost Airlines through Text Mining"* by Liau and Tan (2020), focuses on the Malaysian Low-Cost Carrier (LCC) sector, with a particular emphasis on how airlines can leverage Twitter data to improve customer relationship management (CRM).

The context for this study is the rapid growth of the LCCs sector following airline deregulation, particularly in Asia, where increasing middle-class populations have driven high demand for affordable air travel. Malaysian LCCs, including prominent players such as AirAsia, have become central to the region's tourism and economic development. In this highly competitive environment, Liau and Tan (2020) argue that understanding customer sentiment through social media is a strategic necessity, as it offers real-time, credible, and large-scale feedback that traditional surveys cannot match.

The authors collected over ten thousand tweets during a two-and-a-half-month period on five Malaysian LCCs: AirAsia, Berjaya Air, FireFly, MASwings, and Malindo Air. To analyze this dataset, they employed text mining techniques, combining sentiment analysis and clustering algorithms. The sentiment analysis phase involved two main approaches: a naïve algorithm that counted positive and negative opinion words and the more advanced *SentiStrength tool*, which assessed the intensity of sentiment on a scale from -5 (extremely negative) to +5 (extremely positive). Both approaches revealed that, overall, customer sentiment toward Malaysian LCCs was more positive than negative, even though a bulk of tweets were classified as neutral, as shown in Figure 13 below.

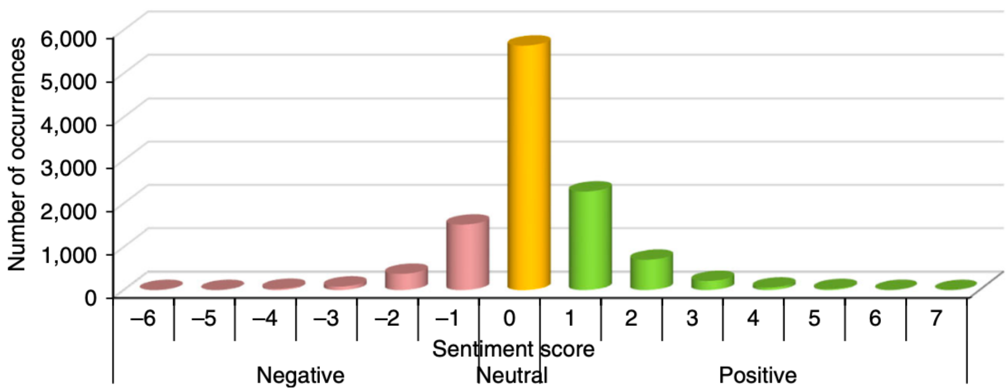


Figure 13: Sentiment scores for Malaysian LCCs using a naïve algorithm (Liau & Tan, 2020)

The clustering analysis, conducted using both K-Means and spherical K-Means algorithms, identified four leading themes in customer tweets: customer service, ticket promotions, flight cancellations and delays, and post-booking management. Customer service emerged as the most frequently discussed topic, reflecting both recommendations for positive experiences and complaints about slow responses or lack of follow-up. Promotions were generally viewed positively, though technical difficulties during high-traffic periods frustrated some of the customers. Unsurprisingly, flight delays and cancellations attracted the most negative sentiment, with passengers expressing dissatisfaction over poor communication and inadequate compensation. Finally, post-booking management highlighted the rising role of social media as a customer service channel, with many customers turning to Twitter to try to solve issues related to booking modifications and refunds. The authors conclude that airlines can leverage these insights for improving customer service training, upgrading web infrastructure during promotional campaigns, and enhancing communication during operational disruptions. By proactively monitoring social media, LCCs can respond more effectively to customer concerns, enhance brand loyalty, and strengthen their competitive position.

2.4.3 Case study 3: passenger satisfaction in U.S. full-service airlines from structured survey data

As the final case study, I choose to examine the paper by Tri Noviantoro and Jen-Peng Huang (2022), titled *"Investigating Airline Passenger Satisfaction: Data Mining Method,"* published in *Research in Transportation Business & Management*. This study provides a contemporary and data-driven perspective on how airlines can identify and improve key service attributes that impact passenger satisfaction using machine learning techniques.

The authors ground their work in the context of an increasingly competitive aviation market, where price wars alone can no longer guarantee long-term competitive advantage. As previous studies have shown, service quality has become a decisive factor in shaping passengers' choices, satisfaction, and loyalty (Chen et al., 2021), so the authors go a step further by leveraging big data analytics to identify the specific service aspects that matter most to travelers, especially for Full-Service Network Carriers. The study employs a rich dataset from Kaggle, which includes over 129,000 survey responses from passengers on U.S. full-service airlines in 2015, capturing a range of demographic and flight-related attributes, as well as ratings on 14 different service categories (e.g., in-flight Wi-Fi, baggage handling, online booking, in-flight entertainment, seat comfort, and cleanliness). Importantly, the authors simplify satisfaction into a binary outcome by combining dissatisfied and neutral responses into one group to focus on the distinction between satisfied and unsatisfied passengers. Methodologically, the paper's major innovation lies in applying feature selection and supervised machine learning algorithms to identify and rank the most predictive service attributes for passenger satisfaction, as demonstrated in Figure 14 below.

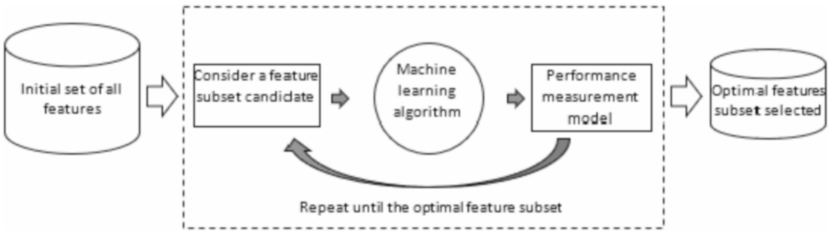


Figure 14: Workflow for feature selection in passenger satisfaction modeling (Noviantoro & Huang, 2022)

The feature selection process consistently identifies four areas for improvement: (1) online/mobile boarding, (2) in-flight Wi-Fi service, (3) baggage handling, and (4) in-flight entertainment. These findings align with emerging passenger demands in the digital age, where convenience, connectivity, and comfort are paramount. Notably, online boarding emerges as the strongest predictor across all models, reflecting passengers' desire for streamlined, paperless, and time-saving processes at the airport. Among the tested classifiers, deep learning models deliver the highest predictive performance, even when limited just to the top five features, underscoring their value in large-scale customer satisfaction research.

From a managerial perspective, the study offers actionable insights. Airlines are advised to prioritize investments in digital services, particularly mobile boarding, and to enhance in-flight connectivity and entertainment options. Improvements in baggage handling processes, potentially through automation and artificial intelligence, are also emphasized as key drivers of passenger satisfaction. Collectively, these service enhancements can strengthen customer loyalty and provide a sustainable competitive advantage in a saturated market.

Chapter 3: Experimental Research

3.1 Theoretical background

As previously discussed, in recent years, academic literature has highlighted the increasing relevance of electronic word-of-mouth (eWOM) in shaping brand perception and influencing consumer decision-making, particularly in the service-dominated industry (Litvin et al., 2008; Jalilvand & Samiei, 2012), like the aviation sector. Understanding consumer dissatisfaction in this industry, particularly in extreme cases, requires grounding in three interrelated domains: electronic word-of-mouth (eWOM), service quality perception, and consumer trust in digital environments. This section, by summarizing the core theoretical and empirical contributions from previous chapters, identifies specific underexplored areas or research gaps in the existing literature. These gaps guide the development of the present study's research questions, which aim to improve the understanding of consumer dissatisfaction in the European airline industry through the lens of extreme negative reviews.

3.1.1 Research gaps and questions

The transformation from traditional word-of-mouth to electronic word-of-mouth (eWOM) has reshaped how consumers evaluate service providers, especially in high-risk, experience-based sectors like aviation. eWOM, defined as informal communication transmitted via digital platforms (Litvin et al., 2008), is now regarded as a critical factor in purchase decisions—especially when trust in brand-generated content is low (Stephen & Galak, 2012; Jalilvand & Samiei, 2012). Reviews shared through online platforms have the potential to influence brand perception, particularly due to their perceived authenticity, volume, and reach (Cheung & Thadani, 2012; Gvili & Levy, 2016).

In Chapter 1 it has been highlighted that negative word-of-mouth (NWOM), particularly in digital form, has a disproportionately strong impact on consumer attitudes and behavioral intentions compared to positive WOM (Richins, 1983, 1984; Herr et al., 1991). Dissatisfied customers often report operational failures, emotional distress, or unmet expectations with greater intensity than satisfied users (TARP, 1986; Kalamas et al., 2008). However, all previous studies are based on all the reviews available, making it more difficult to understand the causes of extreme dissatisfaction. This is why I decided to carry out the first to focus only on one-star reviews written in English on Trustpilot, thereby centering on the most intense expressions of customer dissatisfaction, which tend to contain richer, emotionally charged, and more diagnostic content. This approach aligns with psychological and marketing literature emphasizing that individuals are more motivated to leave reviews after experiencing strong negative emotions such as frustration or betrayal (Wetzer et al., 2007; Kalamas et al., 2008). Moreover, negative reviews are generally perceived as more diagnostic and influential than positive ones when consumers evaluate high-risk or experience-based services such as flights (Herr et al., 1991; Lee & Cranage, 2014). Therefore, by targeting this extreme segment, the study aims to extract the *root causes* of dissatisfaction, offering deeper managerial and academic insights.

In Chapter 2, the literature has again underlined the growing strategic importance of online reviews in the airline industry. According to recent data, 88% of passengers consult reviews when choosing an airline (YouGov, 2023). Compared to traditional quality ratings, user-generated content offers more immediate, granular, and experience-driven insights. However, most academic work remains focused on platforms such as Skytrax or Twitter, leaving review sites like Trustpilot underexplored, despite their high visibility and usage among European consumers. In fact, in 2024 Trustpilot hit 300 million consumer reviews globally as they define themselves as the "The world's largest independent platform for customer feedback", with more than 61 million reviews written in 2024, and with a survey of US consumers demonstrating that 71% of them agreed that a good Trustpilot score makes them more likely to buy from a brand. Moreover, as it can be recalled from Chapter 1, trust emerged as a foundational construct in digital brand evaluation. Indeed, in online review ecosystems, consumer trust is influenced both by source credibility and platform characteristics (Flanagin & Metzger, 2013; Cao et al., 2018). Review platforms vary in their openness, verification systems, and review valence distribution (Kirilenko et al., 2024), all of which shape consumer perceptions of reliability and truthfulness. While platforms like Skytrax and Booking.com often restrict reviews to verified users, others like Trustpilot allow broader participation, sometimes at the cost of perceived credibility (Deng et al., 2021). Nonetheless, their large user base and high traffic make them invaluable repositories of unsolicited feedback. This makes Trustpilot the perfect candidate for my thesis. Moreover, the majority of the studies analyzing online reviews have adopted sentiment analysis approaches, often overlooking the nuanced thematic structures and contextual drivers behind extreme dissatisfaction.

Third, the current segmentation frameworks in airline research tend to distinguish primarily between Full-Service Network Carriers (FSCs), also called legacy airlines, and Low-Cost Carriers (LCCs) (Holloway, 2008; O'Connell & Williams, 2005). However, I decided to introduce a new type of airlines called **Value Carriers** that strategically position themselves between the two traditional categories by offering moderate service levels at competitive prices, typically in regional markets. These hybrid carriers often defy simplistic classification, leading to their exclusion or misrepresentation in comparative analyses. By explicitly including Value Carriers as a third category, this research introduces a more precise segmentation that enables meaningful cross-category comparisons. This refined categorization is particularly useful for investigating anomalies observed during the initial data screening, where some Low-Cost Carriers received higher average ratings than traditional full-service airlines.

Lastly, prior studies have generally adopted a global or country-specific lens, often focusing on markets like North America or Asia while neglecting the European context, despite its regulatory complexity and unique consumer expectations (Punel et al., 2019; Quan et al., 2023). This research focuses on airlines operating in or connected to the European market - meaning offering flight routes to/from European countries - thereby capturing a more geographically relevant and underexplored perspective.

To summarize, the present study addresses four key gaps in the literature:

- Platform underrepresentation: lack of studies analyzing airline reviews on Trustpilot.
- Extreme dissatisfaction focus: limited attention to one-star reviews that offer rich, emotionally charged feedback.
- New segmentation: introduction of Value Carriers to bridge the gap between full-service and low-cost models
- Regional specificity: deliberate focus on airlines operating within or connected to the European market

From these gaps, the main research question arises: **What are the main sources of customer dissatisfaction in one-star airline reviews on Trustpilot, specifically for carriers operating in the European market?**

Additionally, the research seeks to explore: **What differences, if any, exist in the nature and frequency of dissatisfaction across full-service, low-cost, and value carrier categories? Are there any common themes that transcend these classifications?**

By answering these questions, the study contributes to a more comprehensive understanding of consumer dissatisfaction in the European airline sector and provides actionable insights for service improvement across different business models.

3.2 Methodology

The aim of this study is to explore the underlying causes of extreme consumer dissatisfaction in the European airline sector. To do so, this research adopts a mixed-method text mining approach based on unsupervised machine learning techniques. Specifically, the analysis focuses on one-star

English-language airline reviews collected from Trustpilot, a platform largely underexplored in the literature despite its popularity and consumer reach.

The rationale behind this approach lies in the limitations of traditional sentiment analysis. While sentiment analysis has been extensively used in prior literature to measure overall positivity or negativity (e.g., Liau & Tan, 2020; Quan et al., 2023), it does not reveal *why* customers are dissatisfied. Instead, this thesis applies topic modeling, which offers a more nuanced exploration of large unstructured datasets (i.e., large collections of documents) by identifying hidden thematic structures and thus providing a way to organize, understand and summarize large collections of textual information (Abdelrazek et al., 2022).

3.2.1 Topic modeling and Latent Dirichlet Allocation (LDA)

Topic modeling is an unsupervised machine learning technique used in text mining to automatically detect abstract topics from a large body of text of unstructured textual data. A topic, in this context, is defined as a cluster of words that frequently occur together across multiple documents. The key strength of topic modeling is that it summarizes the content of a corpus by revealing its most recurrent themes, without any need for predefined categories or human annotations (Blei, Ng, & Jordan, 2003). This approach is considered exploratory and bottom-up, meaning that it allows researchers to discover structure in the data organically, rather than imposing external assumptions. Each document (i.e., review) is assumed to be composed of a mixture of topics, and each topic is represented by a set of characteristic words. These outputs provide:

1. Topic distributions per document: the probability that a specific review belongs to each identified topic (probabilities sum to 1).
2. Word distributions per topic: the probability of each word appearing within a specific topic, which is crucial for interpreting the semantic meaning of each topic.

To implement this, the study uses Latent Dirichlet Allocation (LDA), a probabilistic model developed by Blei et al. (2003).

LDA is based on two core principles:

1. Each document is a mixture of latent topics.
2. Each topic is a distribution over words, where certain words have higher likelihoods of occurring.

In operational terms, LDA uses Gibbs Sampling, an iterative estimation technique. Initially, words are randomly assigned to topics. Then, for each word in each document, the algorithm recalculates its topic assignment by considering:

- The probability of the topic appearing in the given document.
- The probability of the word appearing in that topic across the corpus.

These assignments are updated repeatedly until the model converges to a stable solution (Blei, 2012).

LDA offers three major advantages (Hu et al., 2018; Blei, 2012):

- It models complex topics by using multiple representative words.
- It captures semantic subtleties by assigning weights to words within each topic.
- It deals with word ambiguity, allowing the same word to appear in multiple topics with varying probabilities.

However, LDA is based on several key assumptions:

- The bag-of-words assumption: word order is ignored.
- The number of topics (K) must be set in advance.
- Each document's topic probabilities sum to one, implying that not all topics will be equally present in all documents.
- The model's outcome can be sensitive to hyperparameter values—namely, alpha (α) and beta (β):
  - α (alpha) controls the topic distribution per document. A low alpha favors sparse topic distributions (i.e., one dominant topic per review), while a high alpha assumes mixed-topic documents. A common benchmark is $\alpha = 0.1$ (Griffiths & Steyvers, 2004).
  - β (beta) controls word distribution per topic. A lower beta (e.g., 0.01) creates more distinctive, coherent topics by reducing word overlap across topics—often preferred in marketing and consumer research for interpretability.

Choosing the right number of topics (K) is a critical step. This study uses a range-based, data-driven approach, guided by:

- Perplexity and log-likelihood scores (Tirunillai & Tellis, 2014),
- Semantic coherence (Mimno et al., 2011),

- The elbow method and manual interpretability checks (e.g., topic distinctiveness and thematic saturation).

Common outputs from LDA can include: a Table of reviews with assigned topic probabilities, a list of top words per topic, used for interpretation, and a fit log showing convergence behavior across iterations.

The analysis was conducted in KNIME, a visual data science platform that allows for parameter tuning, topic exploration, and model validation through additional tools such as topic explorer and word intrusion tests for assessing topic quality (Hu et al., 2018; Cardamone, 2024).

By applying LDA to one-star airline reviews, this research aims to uncover and interpret core dissatisfaction drivers and assess whether and how these differ across full-service, low-cost, and value carrier categories. This technique complements existing models of service quality and eWOM by offering scalable, interpretable, and replicable insights into real customer grievances—often more revealing than structured surveys or numerical ratings alone.

3.2.2 Data Collection

To build the dataset used in this study, a structured web scraping protocol was developed to extract user-generated content from Trustpilot. The aim was to collect one-star reviews written in English for airlines operating flights to and from Europe. The process was conducted in several phases, combining manual mapping, platform-based filtering, and automated scraping.

Data scraping (also referred to as web scraping) is an automated process used to extract large volumes of information from websites. This technique is particularly effective for gathering unstructured textual data from online platforms where content is not available for direct download (Hong & Park, 2019; Xu & Li, 2016). In research contexts, scraping enables the collection of user-generated data at scale, facilitating empirical analyses of real-time consumer experiences and behaviors.

The initial phase consisted of identifying all airlines operating in the European market. This was done by consulting the official IATA (International Air Transport Association) listings and subsequently verifying airline activity and availability through their respective official websites. An Excel file was compiled listing all candidate airlines. Each airline was then manually searched on Trustpilot to evaluate its relevance for inclusion in the study. For each airline, three variables were collected and used to inform the selection:

- Average rating (stars)
- Number of English-language reviews
- Number of one-star English-language reviews

While the average rating provided preliminary insight into general customer perception, the two language-specific variables were critical for ensuring data suitability. Given that the thesis is written and analyzed in English, only airlines with a substantial number of English-language reviews were considered. Specifically, the inclusion criterion required **at least 100 one-star reviews in English** per airline. This threshold was chosen to ensure content representativeness and sufficient text volume for meaningful topic modeling analysis. Airlines that did not meet these conditions were excluded from the final sample.

Airlines		
Aegean Airlines	Emirates	Pegasus Airlines
Aer Lingus	Ethiopian Airlines	Philippine Airlines
Aeroitalia	Etihad Airways	PLAY
Aeromexico	Eurowings	Qatar Airways
Air Arabia	Finnair	Royal Air Maroc
Air Canada	flydubai	Royal Jordanian
Air Europa	Gulf Air	Ryanair
Air France	Iberia	SAS
Air India	Icelandair	Scoot
Air Mauritius	IndiGo	Singapore Airlines
Air Serbia	ITA airways	Sky Express
Air Transat	Jet2	SriLankan Airlines
AirAsia	JetBlue Airways	SunExpress
AirBaltic	Kenya Airways	TAP Air Portugal
American Airlines	KLM	Thai Airways
Austrian Airlines	Kuwait Airways	Transavia
Avianca	LATAM Airlines	Turkish Airlines
British Airways	LEVEL	United Airlines
Brussels Airlines	LOT Polish Airlines	Vietnam Airlines
Cathay Pacific	Lufthansa	Virgin Atlantic
Czech Airlines	Malaysia Airlines	Volotea
Delta Air Lines	Norse Atlantic	Vueling
EasyJet	Norwegian Air Shuttle	WestJet
Egyptair	Oman Air	Wizz Air

Figure 15: Final list of selected airlines for analysis (own elaboration)

Once the final list of airlines was established, as shown in Figure 16 above, it counted 72 airlines total. Afterwards, the data collection started and was performed using Octoparse, a no-code platform. The scraping logic was structured to reflect Trustpilot's review architecture, which presents content in paginated batches of 20 reviews per page. Octoparse was configured to perform the following tasks:

1. Navigate to the filtered Trustpilot page (already set to English language and one-star reviews).
2. Scroll through visible content to ensure that lazy-loaded elements were fully rendered.

3. Loop through each review element, extracting specific fields (e.g., title, text, date).
4. Paginate to the next page and repeat the process until all available reviews were collected.

The following visual diagram (Figure 17) summarizes the scraping process logic as configured in Octoparse.

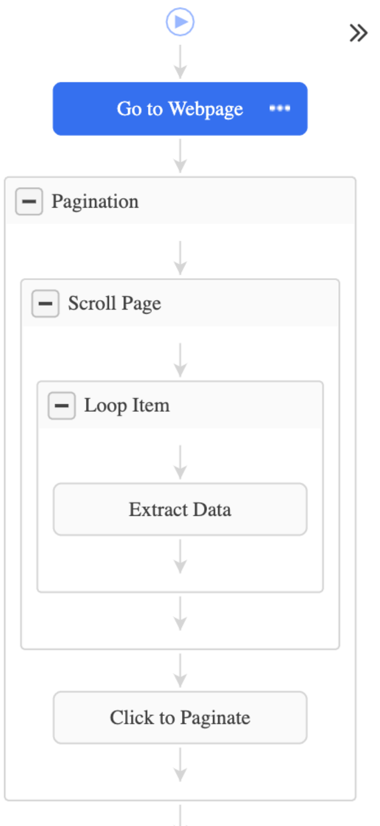


Figure 16: Visual representation of the Octoparse scraping process

This modular setup ensured that all reviews were extracted reliably, including those nested on subsequent pages, without triggering anti-bot protection mechanisms or compromising data quality.

Each execution of the workflow generated an Excel file containing the following variables:

- Review title
- Review URL
- Username
- Username country
- Number of reviews by user
- Time posted
- Typography (verified or not verified review)
- Review text
- Experience date

- Reply date (if applicable)
- Reply text (if applicable)
- Useful count
- Page URL

review_title	review_url	username	username_c	username_re	time_posted	typography_t	review_text	experience_	reply_date	reply_text	useful_count	Page_URL
Rubbish polic	https://www.	CollectPlus (	GB	4 reviews	11 hours ago	Invited	Rubbish polic	May 22, 2025				https://www.trustpilot.c
No refunds..	https://www.	Chris h	GB	1 review	13 hours ago	Invited	Attempted to	May 22, 2025				https://www.trustpilot.c
Give us the p	https://www.	J.fading Jo	SE	2 reviews	15 hours ago	Invited	Give us the p	May 22, 2025				https://www.trustpilot.c
Absolute was	https://www.	Matthew Gill	NL	5 reviews	17 hours ago	Invited	Absolute was	May 22, 2025	7 hours ago	Hi,Thanks for		https://www.trustpilot.c
Terrable cust	https://www.	Paul Deamer	GB	51 reviews	18 hours ago		Terrable cust	May 13, 2025				https://www.trustpilot.c
awful custom	https://www.	Mr Terry Woo	GB	10 reviews	18 hours ago	Invited		May 22, 2025				https://www.trustpilot.c
Agent not aw	https://www.	Shannon Grif	IE	2 reviews	19 hours ago	Invited	The Agent de	May 22, 2025	7 hours ago	Hi,Thanks for		https://www.trustpilot.c
No help	https://www.	Trish	GB	2 reviews	A day ago	Invited	No help. Ager	May 22, 2025	7 hours ago	Hi,Thanks for	1	https://www.trustpilot.c
EASYJET tax e	https://www.	jose.fabiao	PT	1 review	A day ago	Invited	Easy jet runs	May 22, 2025	7 hours ago	Hi,Thanks for		https://www.trustpilot.c
Sad to say, w	https://www.	K Furr	GB	10 reviews	A day ago		•Am stopping	May 13, 2025				https://www.trustpilot.c
I have not res	https://www.	sandra	GB	4 reviews	A day ago	Invited	I have not res	May 22, 2025	7 hours ago	Hi,Thanks for		https://www.trustpilot.c
not resolved	https://www.	jacquelineha	GB	1 review	A day ago	Invited		May 22, 2025				https://www.trustpilot.c
Poor custome	https://www.	clarke	GB	1 review	2 days ago	Invited	Person acted	May 21, 2025	A day ago	Hi,Thanks for		https://www.trustpilot.c
You can't,I wa	https://www.	janehodges	ES	1 review	2 days ago	Invited	You can't,I wa	May 21, 2025	A day ago	Hi Jane,Than		https://www.trustpilot.c
Terrible custo	https://www.	Barry Elder	GB	3 reviews	2 days ago	Invited	I have the cha	May 21, 2025	A day ago	Hi Barry,Thar		https://www.trustpilot.c
Holiday from	https://www.	Louise Marsh	GB	1 review	2 days ago		Just returned	May 03, 2025	A day ago	Hi Louise,Tha		https://www.trustpilot.c
Damage to pı	https://www.	Ellie	GB	5 reviews	2 days ago		We had an ou	May 01, 2025	A day ago	Hi Ellie,Thanl		https://www.trustpilot.c
Nine hours la	https://www.	Sebastian Ka	GB	4 reviews	2 days ago		On Decembe	December 2	A day ago	Hi Sebastian		https://www.trustpilot.c
The whole po	https://www.	Terence Foul	GB	12 reviews	2 days ago	Invited	The whole po	May 21, 2025	A day ago	Hi Terence,Tl		https://www.trustpilot.c
My daughter	https://www.	Vicky Amos	GB	1 review	2 days ago		My daughter	May 08, 2025	A day ago	Hi Vicky,Thar		https://www.trustpilot.c
Easyjet is not	https://www.	Nicola Armel	NL	1 review	2 days ago	Invited		May 21, 2025	A day ago	Hi Nicola,Tha		https://www.trustpilot.c
poor custome	https://www.	Jay ar	PH	1 review	2 days ago	Invited		May 21, 2025	A day ago	Hi,Thanks for		https://www.trustpilot.c
Worst service	https://www.	ManaliChaw	GB	3 reviews	2 days ago		Worst service	May 15, 2025	A day ago	Hi,Thanks for		https://www.trustpilot.c
Update pictu	https://www.	Rachel Perki	GB	1 review	2 days ago		Please updat	May 10, 2025	A day ago	Hi Rachel,Th		https://www.trustpilot.c
Frustration o	https://www.	David Albouy	FR	1 review	2 days ago	Invited	You should be	May 21, 2025	A day ago	Hi David,Tha		https://www.trustpilot.c
I did not like t	https://www.	Nelson	PT	5 reviews	2 days ago	Invited	I did not like t	May 21, 2025				https://www.trustpilot.c
Passed on to	https://www.	Catherine Br	GB	1 review	2 days ago	Invited		May 21, 2025				https://www.trustpilot.c
Awful	https://www.	Terry	GB	1 review	2 days ago	Invited	Really bad se	May 21, 2025				https://www.trustpilot.c
Très simpatic	https://www.	Divananoee	FR	1 review	2 days ago	Invited	Très simpatic	May 21, 2025				https://www.trustpilot.c
Fekezda got (	https://www.	Newbie EASY	US	1 review	2 days ago	Invited	Fekezda got (	May 21, 2025				https://www.trustpilot.c
explaining fo	https://www.	Sharon A.	MA	1 review	2 days ago	Invited	I was explain	May 21, 2025	2 days ago	Hi Kola,Thanl		https://www.trustpilot.c
the operator	https://www.	Nunzia and C	MA	1 review	2 days ago	Invited	the operator	May 20, 2025	2 days ago	Hi,Thanks for		https://www.trustpilot.c
2 hours on th	https://www.	Anna Clause	GB	8 reviews	2 days ago		2 hours on th	April 20, 202	2 days ago	Hi Anna,Than		https://www.trustpilot.c
I didnt receiv	https://www.	Anon	GB	3 reviews	3 days ago		I didnt receiv	May 20, 2025	2 days ago	Hi,Thanks for		https://www.trustpilot.c
I asked to car	https://www.	Mrs A LUCK	GB	10 reviews	3 days ago	Invited	I asked to car	May 20, 2025	2 days ago	Hi Alexis,Tha		https://www.trustpilot.c

Figure 17: Example of a Trustpilot excel output from EasyJet

Notably, the inclusion of the reply content was intentional, as it may reveal patterns in how different carriers respond to customer dissatisfaction. The useful count, which ranges from 1 to 5, indicates how helpful other users found the review, offering another potential proxy for perceived relevance or impact.

Lastly, the output - so the total number of reviews downloaded - was manually verified by matching the total number of extracted reviews with the count reported on the Trustpilot interface. This verification step ensured completeness and integrity in the dataset used for topic modeling.

In the end, I ended up sampling 72 airlines, for a total of 99176 one-star English reviews.

3.2.3 Data Processing

I relied on the KNIME Analytics Platform to do the topic modeling. It's an open-source, visual, workflow-based program that is often used for data analysis, including text mining. Its modular design makes it easy to combine different processes in the data processing process, which makes it good for working with a lot of unstructured text data.

The data processing workflow comprised several key stages:

1) **Data preparation**
2) **Data Pre-processing**
3) **Find the optimal number of topics**
4) **Execute LDA**

The first step is to get the data ready for topic modeling. This involves essentially a series of steps for the preparation (Figure 19) and pre-processing (Figure 20) to get textual data ready for topic modeling methods like latent Dirichlet allocation (LDA). The objective of these steps is threefold: firstly, to clean the raw review data; secondly, to standardize it; and thirdly, to transform it into a format suitable for LDA analysis.

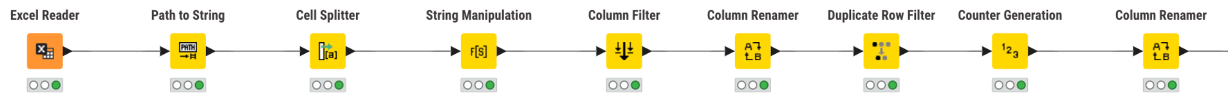


Figure 18: Data preparation process on KNIME

The Excel reader node was used to bring in all 72 Excel files, which were the airline's datasets. Each file corresponded to a distinct airline and contained English-language reviews of one star that had been previously extracted from Trustpilot. To make it easier to find the airline that each review is about, the file names were changed so that they simply included the airline's name. I used the string manipulation node to get rid of the ".xlsx" extension, resulting in a clean "brand" identification for each review. Next, the duplicate row filter node was added to make sure the data was correct by removing any duplicate rows. This technique cut the dataset from 99,373 reviews to 99,176 unique reviews, making sure that each review was only counted once in the study. Finally, a counter node was added, which made a new column and gave each observation or review a unique ID. Then, this "Counter" column was given the name "id." These processes for cleaning are crucial to make sure that the analysis is based on reviews that are unique and appropriately identified.

After completing this first stage, the next step was to change the text data into a format that could be used for topic modeling using five metanodes (nodes that contain sub-workflows).

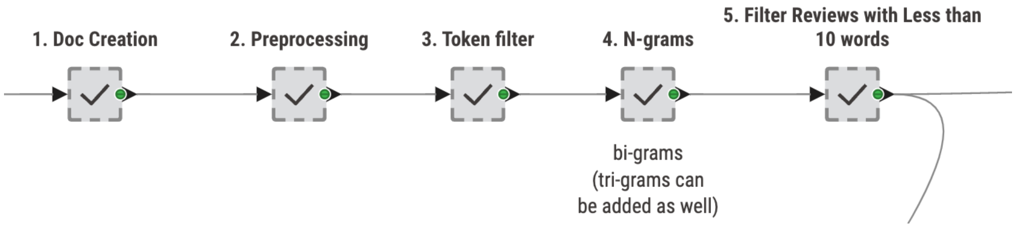


Figure 19: Data pre-processing metanodes on KNIME

The first metanode is labeled **Document Creation**, Inside it, there are the strings that turn text-based reviews (in the column called Text) into a document format, with the brand column serving as the category. This change is necessary for the next phases in KNIME's text processing. Next, the **Preprocessing** pipeline included several standard nodes:

- Punctuation Erasure: took away punctuation marks to prevent them from being treated as separate tokens.
- Number Filter: removed numbers that don't add to the meaning of the topic.
- Case Converter: converted all text to lowercase to ensure uniformity.
- Stop Word Filter: Removed common stop words (e.g., "the," "and," "but") that don't add any meaning.
- Snowball Stemmer: reduced words to their root forms, helping in the consolidation of similar terms (e.g., "delayed," "delays," "delay" become "delay").

These preprocessing steps are critical in reducing noise and dimensionality in the textual data, thereby enhancing the quality of the topic modeling output (Silipo, 2021).

To further refine the dataset, a **Token filter** metanode was added. It is a crucial customizable step prior to LDA. The technique involves using several filters to get rid of words that are thought to be of little informational value (tokens). The first filter is a means to manually remove certain phrases from the analysis: using a Table creator node, I made a list of non-informative terms (e.g., "airline," "airways," specific airline names) to be excluded from the analysis. The rationale behind this manual selection was to keep phrases that were first recognized as prevalent in topic modeling outputs from overshadowing more important topics. The second and third filters are based on frequency: terms that appeared too often across documents (above a set threshold, e.g., 70%) were removed, as they probably reflected general ideas that weren't helpful for separating themes. Conversely, terms that appeared infrequently (below a minimum occurrence threshold, e.g., five times) were also left out to get rid of noise from unusual words. This iterative process of vocabulary refinement is essential in enhancing the coherence and interpretability of the resulting topics (Bystrov et al., 2023).

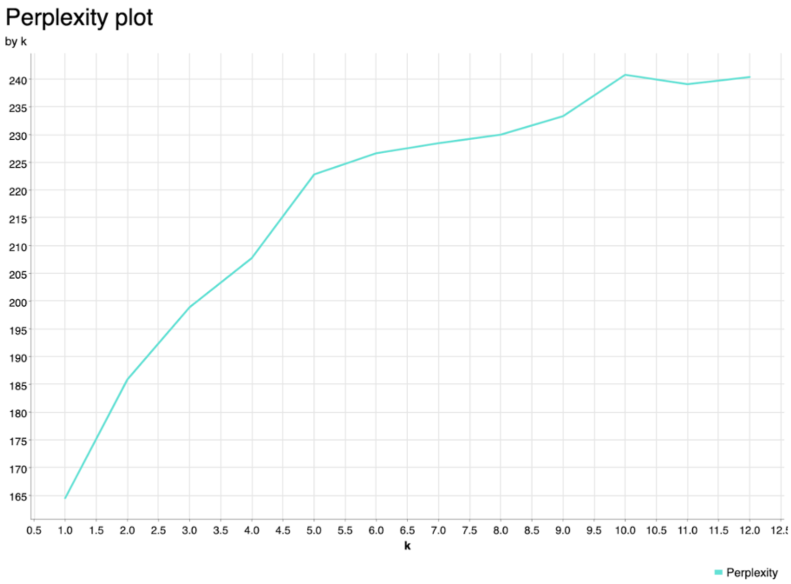
Following the implementation of token filtering and recognizing that certain concepts are better captured through combinations of words (e.g., "customer service," "flight delay") a metanode was employed for **N-grams**, i.e., word combinations, to generate bi-grams (two-word combinations). After that, the n-grams were sorted by how often they appeared, and I decided to keep only the combinations that made the most sense, the ones that appeared at least 20 times. Adding n-grams to the text representation makes it more interesting by including multi-word phrases that single tokens would overlook, to give a better grasp of the themes.

Finally, to ensure that the reviews contained sufficient information for meaningful topic extraction, reviews containing less than ten words were filtered out. Short reviews often lack the context necessary for accurate topic modeling and can introduce noise into the analysis.

After the workflow has cleaned up the text input, the LDA is used to do topic modeling. Finding the right number of topics (K) is a very important part of topic modeling with Latent Dirichlet Allocation (LDA). The quality, interpretability, and analytical usefulness of the model that comes out of this choice are all directly affected. If you choose too few subjects, you can end up with groups that are too broad and don't show major differences in the data. On the other hand, if you choose too many topics, you might end up with themes that are broken up or repeated and hard to understand (Blei et al., 2003; Griffiths & Steyvers, 2004).

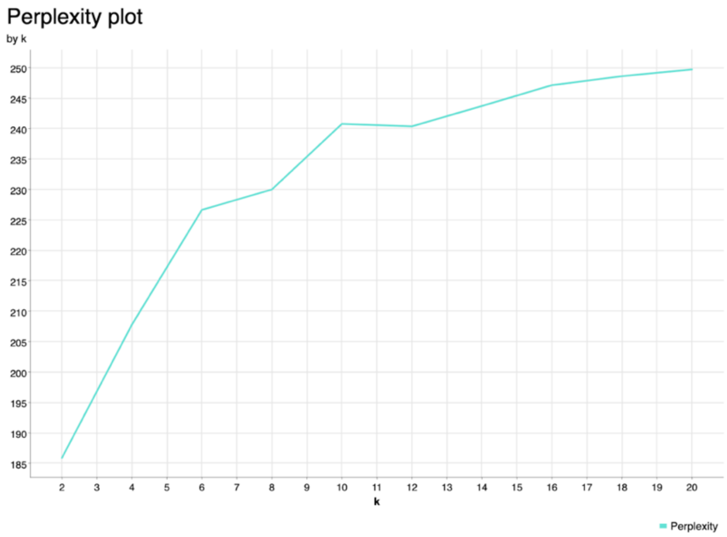
One frequently used methodology for this purpose is the **elbow method**, which, when combined with the **perplexity index**, gives a heuristic for determining the point at which increasing the number of topics yields diminishing gains in model performance. In fact, perplexity is a statistical way to measure how well a probabilistic model like LDA predicts a sample. A lower perplexity score means that the model is better at predicting how words will be spread out in new documents, which means it fits the data better (Blei et al., 2003). It is also widely agreed that confusion alone should not be the only factor in the final decision. In applied research, especially when dealing with consumer feedback, interpretability and semantic coherence are still quite important (Chang et al., 2009; Mimno et al., 2011). The elbow approach plots the perplexity scores against a range of topic numbers. At first, when the number of subjects goes up, the perplexity goes down a lot, which means the model is doing better. But beyond a certain point, the rate of improvement slows down and the curve flattens out. The point on the plot where this shift in rate happens looks like an elbow. This is the best number of subjects, as it strikes a balance between model complexity and performance (Thorndike, 1953).

I made a custom loop to test a range of possible K values by executing LDA many times at the same time. The workflow contained a Table creator that gave a list of K values to look at. At first, these numbers were from 2 to 10, but they were later expanded to encompass a wider range for robustness. The parallel LDA node used α = 0.1 and β = 0.01 to figure out the topic model for each value of K. I used the Line Plot (JavaScript) node to record and display the resulting perplexity values to make it visually easier to find the elbow. Then I build up the Table maker node in three different ways. The first time used 2 to 10 numbers (see Graph 2), the second used even numbers from 2 to 20 (see Graph 3), and the third used numbers from 2 to 40 (see Graph 4). This method was chosen to make sure that the analysis was thorough and detailed. The three graphs are displayed below.

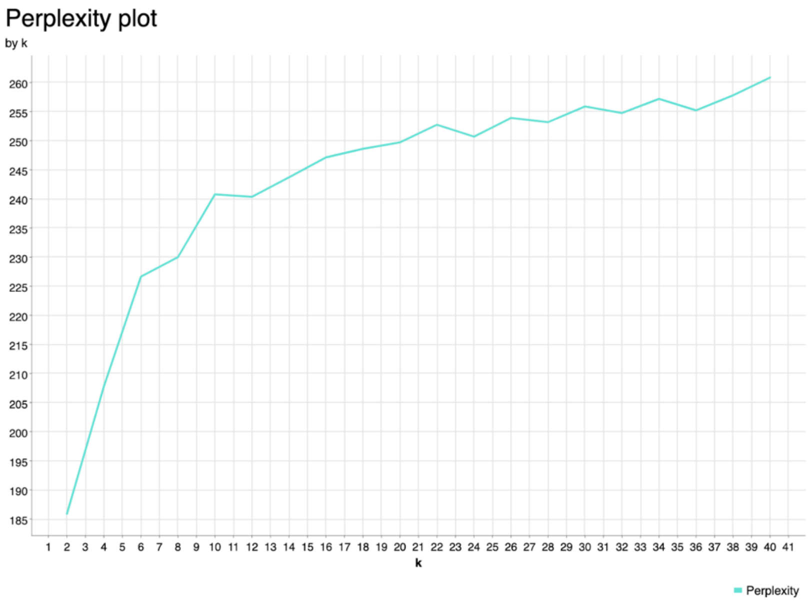


Graph 2: Perplexity plot for topic numbers ranging from 2 to 10

Graph 2 above shows that perplexity lowers quickly between K = 1 and K = 6, but the improvement slows down a lot after K = 7. After that point, the curve starts to level off, showing that adding more subjects doesn't help much with the statistical fit.



Graph 3: Perplexity plot for topic numbers ranging from 2 to 20



Graph 4: Perplexity plot for topic numbers ranging from 2 to 40

After going over the perplexity plots (Graph 2, Graph 3, Graph 4) several times and looking them over carefully, I found that, from my point of view, the inflection point was between K = 6 and K = 11.

k Number (integer)	Perplexity Number (double)
1	164.511
2	185.884
3	198.893
4	207.771
5	222.815
6	226.645
7	228.433
8	229.987
9	233.314
10	240.765
11	239.078
12	240.364
12	240.364

Table 5: Perplexity scores for topic numbers ranging from 2 to 10

There is a sharp rise in perplexity from K = 1 (164.511) to K = 6 (226.645), which shows that the model is getting better at fitting the data. The change in perplexity is significantly lower from K = 6 to K = 11, though, and it starts to level out. The values go up from 226.645 (K = 6) to only 239.078 (K = 11). So, the range from 6 to 11 was chosen for the next qualitative examination.

3.2.4 Topic solution

After finding a potential area for K, the ultimate decision is made by hand using qualitative analysis. I performed LDA with several candidate values of K (like 6, 7, 8, 9, 10, and 11), using a separate LDA node that wasn't part of the Perplexity metanode, and then looked at the list of words that went with each topic for each value of K. The goal is to figure out what each issue means and decide which value of K gives a solution that is easier to understand and convey overall. I chose ten words to describe the topic as the setting.

Among all the configurations tested, I paid special attention to K = 6, K = 7, and K = 8, which seemed to make the most sense. These solutions were manually compared using their respective topic tables, paying close attention to:

- Redundancy between themes (if the same phrases showed up in more than one topic)
- How different each topic seemed to be (i.e., whether each item seemed to cover a different area of unhappiness)
- Use of general or vague terminology that don't provide any information (which can make the topic less clear)

- Fits with what is already known about why people are unhappy with airline service, such as being on time, how staff acts, problems with luggage, and so on.

#	RowID	Topic id String	Concatenate(Term) String
1	Row0	topic_0	seat, plane, food, passenger, staff, service, hour, paid, time, board
2	Row1	topic_1	luggage, airport, day, bag, lost, call, check, baggage, help, arrive
3	Row2	topic_2	customer, experience, passenger, customer-service, provide, lack, compensation, airway, staff, complaint
4	Row3	topic_3	hour, airport, delay, time, day, hotel, plane, arrive, staff, cancell
5	Row4	topic_4	refund, booke, call, try, money, ticket, day, cancell, email, customer-service
6	Row5	topic_5	check, bag, pay, luggage, staff, airport, company, board, people, ticket

Table 6: LDA output for topic solution K=6

The first solution, illustrated in Table 6, for K = 6, appeared to be too broad and comprehensive. Some of the themes put together ideas that weren't clearly related (for example, topic_0 combined difficulties with food, boarding, and service), while some clusters were still imprecise or overlapping (for example, topic_1 and topic_3 both talked about airports and the day) to be relevant for analysis.

#	RowID	Topic id String	Concatenate(Term) String
1	Row0	topic_0	hour, airport, delay, time, hotel, day, plane, arrive, staff, board
2	Row1	topic_1	experience, passenger, customer, provide, airway, staff, lack, situation, travel, customer-service
3	Row2	topic_2	company, customer, money, people, worst, customer-service, service, don't, staff, time
4	Row3	topic_3	call, try, email, phone, customer-service, booke, refund, contact, hour, day
5	Row4	topic_4	check, bag, pay, luggage, airport, board, staff, check-in, ticket, baggage
6	Row5	topic_5	refund, booke, ticket, money, cancell, day, change, pay, paid, company
7	Row6	topic_6	seat, plane, food, passenger, staff, hour, service, paid, meal, drink
8	Row7	topic_7	luggage, bag, day, lost, baggage, airport, claim, arrive, suitcase, damage

Table 7: LDA output for topic solution K=8

On the other hand, the K = 8 solution in Table 7 added noise and redundancy. Terms such as "don't" and "worst" began appearing more frequently—these are emotionally charged but not thematically informative. Also, some subjects were specified excessively narrowly, which caused ideas to overlap or repeat themselves (for example, issues about baggage or compensation showing up twice with different wording in both topic_7 and topic_4).

#	RowID	Topic id String	Concatenate(Term) String
1	Row0	topic_0	seat, plane, food, passenger, staff, service, hour, board, time, experience
2	Row1	topic_1	bag, luggage, check, staff, airport, board, pay, baggage, rude, people
3	Row2	topic_2	experience, customer, passenger, provide, airway, staff, customer-service, travel, lack, situation
4	Row3	topic_3	ticket, booke, pay, change, seat, check, price, paid, try, time
5	Row4	topic_4	refund, money, company, cancell, booke, holiday, customer, day, voucher, travel
6	Row5	topic_5	airport, hour, delay, day, time, hotel, arrive, plane, staff, miss
7	Row6	topic_6	call, email, try, customer-service, refund, phone, day, contact, booke, time

Table 8: LDA output for topic solution K=7

In the end, I thought the K = 7 model, whose results are displayed in Table 8, had the cleanest and most balanced structure. Each sequence of terms covered a different area of customer dissatisfaction without breaking up too much. The top terms made sense and were arranged by theme so that they could be easily understood (for example, one issue was clearly about handling baggage, another was about flight delays, and another was about how to get a refund). This made the 7-topic solution the easiest to understand, the most useful, and the most semantically consistent.

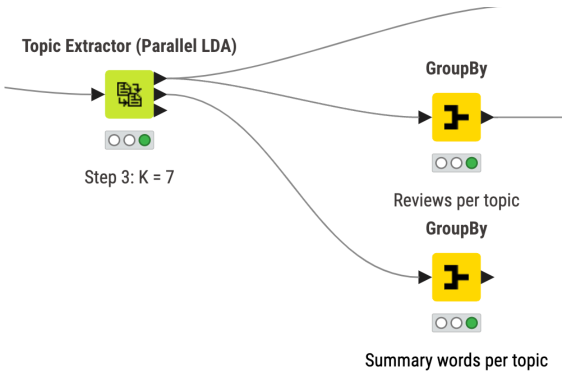


Figure 20: Performing LDA on KNIME

In conclusion, K = 7 was chosen as the model for this investigation. It broke down customer complaints into clear and useful groups, which is a good basis for the more in-depth qualitative analysis in the next chapter. It was then time to give the topics meaningful names based on the most common keywords found by the LDA model after I chose how many topics to include.

Assigned topic	Topic name	Keywords
topic-0	In-Flight Experience	seat, plane, food, passanger, staff, service, hour, board, time, experience
topic-1	Check-in Process	bag, luggage, check, staff, airport, board, pay, baggage, rude, people
topic-2	Customer Service & Support	experience, customer, passanger, provide, airway, staff, customer-service, travel, lack, situation
topic-3	Booking and Payment Issues	ticket, booke, pay, change, seat, check, price, paid, try, time
topic-4	Refunds and Compensation	refund, money, company, cancel, booke, holiday, customer, day, voucher, travel
topic-5	Flight Delays and Scheduling Problems	airport, hour, delay, day, time, hotel, arrive, plane, staff, miss
topic-6	Contact and Communication Channels	call, email, try, customer-service, refund, phone, day, contact, booke, time

Table 9: Assigned LDA topics with corresponding labels and top keywords (own elaboration)

I chose to call the first topic "**In-Flight Experience**" since it comprises a combination of service touchpoints including chair comfort, meals, time, and staff behavior, all of which have to do with the service provided throughout the flight. The second topic, called "**Check-in Process**", is about problems that come up at counters or gates before boarding, especially those that have to do with baggage. For example, fees may be charged for overweight luggage (e.g., "pay") or for luggage that is too big and staff interactions.

The third topic, "**Customer Service & Support**", got its name from the bi-gram "customer-service" and other terms that generally show how people feel about the quality of service (such as "experience" and "lack").

The fourth item, "**Booking and Payment Issues**", covers worries about the full process of making a reservation and paying for it. The fifth category, "**Refunds and Compensation**", collects complaints about ways to get money back, like vouchers or cancellations.

"**Flight Delays and Scheduling Problems**" is the sixth topic. It includes complaints about timing, like delays, missing flights, and trouble rebooking, which often leads to more general displeasure.

Last but not least, "**Contact and Communication Channels**" as a seventh topic may look like the third one, but it focuses on how people get frustrated with their attempts to communicate, like when their calls or emails go unanswered.

These last labels are supposed to be obvious and distinct categories that show the most common and important areas of extreme discontent that airline customers wrote about in one-star Trustpilot reviews.

3.3 Results

Once the best topic number (K = 7) was chosen and the Latent Dirichlet Allocation (LDA) model was run, each topic was given a descriptive label based on its most common phrases, as described in the preceding section.

Importantly, the identification and labeling of these seven distinct themes already provide an answer to the central research question: *What are the main sources of customer dissatisfaction in one-star airline reviews on Trustpilot, specifically for carriers operating in the European market?* The study shows that people are mostly unhappy in seven main areas:

1. In-Flight Experience (topic_0)
2. Check-in Process (topic_1)
3. Customer Service & Support (topic_2)
4. Booking and Payment Issues (topic_3)
5. Refunds and Compensations (topic_4)
6. Flight Delays and Scheduling Problems (topic_5)
7. Contact and Communication channels (topic_6)

The next phase in the analysis was to look at how each topic was spread out across the whole dataset after these thematic groups were made, as shown in Table 10. I utilized a GroupBy node to count how many reviews had each topic as the main theme. This made it possible to discover how often each problem came up in the 82,323 one-star reviews that made up the final corpus. Then, a Math Formula node was used to figure out how often each topic came up in relation to the others. I did this by dividing the number of reviews for each topic by the overall number of reviews, which gave us a normalized proportion between 0 and 1. This metric makes it easier to compare topics directly, which helps find the sources of dissatisfaction that are most and least common in the dataset.

#	RowID	Assigned topic String	Count*(id) Number (integer)	Frequency Number (double)
1	Row0	topic_0	8942	0.109
2	Row1	topic_1	11848	0.144
3	Row2	topic_2	4596	0.056
4	Row3	topic_3	10113	0.123
5	Row4	topic_4	14986	0.182
6	Row5	topic_5	14580	0.177
7	Row6	topic_6	17258	0.21

Table 10: Distribution and frequency of assigned topics in one-star Trustpilot reviews

Contact and Communication Channels are the main cause of dissatisfaction, accounting for 21.0% of all complaints. People often complain about unresponsive help lines, failed attempts to reach customer service, and the feeling that customer service agents are hard to reach in this area. Refunds and Compensation (18.2%) and Flight Delays and Scheduling Problems (17.7%) are the second and third most common subjects, respectively. These themes generally have to do with canceled trips and lost money, both of which make people feel worse and make them less happy with the service. The Check-in Process accounts for 14.4% of the negative reviews and Customer Service & Support for 12.3%. On the other hand, Customer Service & Support (5.6%) and In-Flight Experience (10.9%) are still important but the least talked about. Overall, the results show that operational problems and poor communication after service are the main reasons why passengers are so unhappy. This information is especially useful in areas where experience matters, like air travel, because passengers often can't get help right away or understand what's going on when something goes wrong.

To add analytical depth and interpretive nuance to the topic distribution across airlines, I sorted all 72 carriers in the dataset into three distinct business model types (Table 11):

1) Full-Service Network Carriers (FSNCs) – 18 airlines
2) Low-Cost Carriers (LCCs) – 28 airlines
3) Value Carriers (VCs) – 26 airlines

Brand	Classification	Brand	Classification
Aegean Airlines	VC	KLM	FSNC
AerLingus	VC	Kenya Airlines	VC
Aeroitalia	VC	Kuwait Airlines	VC
Aeromexico	VC	LATAM	VC
Air Arabia	LCC	LEVEL	LCC
Air Asia	LCC	LOT Polish Airline	VC
Air Canada	FSNC	Lufthansa	FSNC
Air Europa	VC	Malaysia Airlines	VC
Air India	VC	Norse Atlantic	LCC
Air Mauritius	VC	Norwegian	LCC
Air Transat	VC	Oman Air	FSNC
AirFrance	FSNC	PLAY Airlines	LCC
AirSerbia	VC	Pegasus Airlines	LCC
American Airlines	VC	Philippine Airlines	VC
Austrian Airlines	VC	Qatar	FSNC
Avianca	VC	Royal Air Maroc	VC
British Airways	FSNC	Royal Jordanian	VC
Brussels Airlines	VC	Ryanair	LCC
Cathay Pacific	FSNC	SAS	VC
Czech Airlines	VC	Scoot	LCC
Delta Airlines	VC	Singapore Airlines	FSNC
Easyjet	LCC	Sky Express	LCC
Egyptian Air	VC	Srilankan Airlines	VC
Emirates	FSNC	SunExpress	LCC
Ethiad Airways	FSNC	TAP Air Portugal	VC
Ethiopian Airlines	VC	Thai Airways	FSNC
Eurowings	LCC	Transvia	LCC
Finnair	VC	Turkish airlines	FSNC
FlyDubai	LCC	United Airlines	FSNC
Gulf Air	VC	Vietnam Airlines	VC
ITA Airways	FSNC	Virgin Atlantic	FSNC
Iberia	VC	Volotea	LCC
Icelandair	VC	Vueling	LCC
Indigo	LCC	Westjet	LCC
Jet2	LCC	Wizz air	LCC
Jetblue	VC	airBaltic	LCC

Table 11: Classification of the 72 airlines in the sample by business model: Full-Service Network Carriers (FSNC), Low-Cost Carriers (LCCs), and Value Carriers (VCs) (own elaboration)

As previously discussed in Section 2.1.2, the first two groups - FSNCs and LCCs - come from well-known frameworks in the aviation literature (e.g., Holloway, 2008; O'Connell & Williams, 2005). FSNCs are known for offering a wide range of services, such as multiple cabin classes, loyalty programs, and hub-and-spoke network structures. LCCs, on the other hand, focus on being affordable and efficient, and they often run point-to-point routes with a simpler service model.

I added a third category called Value Carriers to this study to make the analysis more accurate and to fix the problems with a binary categorization. These airlines usually charge mid-range to low prices, but they try to set themselves apart from LCCs by offering better services or more routes. For example, Aeromexico has direct flights to Rome Fiumicino and long-haul international routes, but it doesn't entirely fit the definition of an FSNC. I found Value Carriers by carefully looking through airline websites, route maps, and service descriptions, as well as how these airlines promote themselves in the market. In this way, the classification is also based on a final decision based on evidence that is available to the public.

This three-part classification system makes it easier to compare how unhappy customers are with different types of businesses. It also helps to look into whether each category fits what customers expect and how any differences affect how good the service seems to be. Later in this chapter, we'll look more closely at these dynamics, especially in terms of how they affect customer experience management strategies.

After figuring out the overall distribution of subjects in the dataset, the study went deeper by looking at how common each topic was at the level of specific airline brands. In this step, we look into how each of the identified dissatisfaction factors, like Flight Delays and Scheduling Problems, Refunds and Compensation, or In-Flight Experience, is spread out among the different airlines that fly to or from Europe. The brand variable, which shows which airline each review is about, was used to arrange the dataset such that this output could be made. The GroupBy node in KNIME was used to find the average value for each topic column in each airline group. This procedure essentially gave me the average subject proportion for each carrier, which created a distribution that shows how important each sort of complaint is for each airline. The tables that came out of this (see Table 12) show this information. Each row is for a different airline, and each column is for one of the seven themes that were found.

brand	In-Flight E...	Check-in P...	Customer ...	Booking a...	Refunds a...	Flight Dela...	Contact C...
Aegean Airlines	0.068	0.237	0.087	0.152	0.153	0.135	0.168
AerLingus	0.089	0.105	0.055	0.07	0.179	0.21	0.292
Aeroitalia	0.044	0.18	0.034	0.193	0.191	0.14	0.219
Aeromexico	0.088	0.092	0.072	0.196	0.238	0.15	0.165
Air Arabia	0.074	0.243	0.131	0.137	0.167	0.117	0.13
Air Asia	0.063	0.111	0.071	0.159	0.222	0.092	0.282
Air Canada	0.131	0.105	0.087	0.118	0.124	0.246	0.188
Air Europa	0.18	0.122	0.078	0.108	0.197	0.106	0.21
Air India	0.233	0.102	0.119	0.094	0.11	0.151	0.191
Air Mauritius	0.148	0.045	0.074	0.085	0.193	0.214	0.241
Air Transat	0.14	0.116	0.086	0.097	0.245	0.134	0.183
AirFrance	0.112	0.153	0.089	0.108	0.122	0.218	0.198
AirSerbia	0.079	0.148	0.071	0.111	0.117	0.312	0.162
American Airli...	0.14	0.138	0.067	0.107	0.141	0.285	0.121
Austrian Airlines	0.103	0.156	0.085	0.119	0.122	0.209	0.207
Avianca	0.119	0.137	0.073	0.196	0.133	0.099	0.243
British Airways	0.14	0.078	0.075	0.101	0.176	0.155	0.276
Brussels Airlin...	0.063	0.119	0.076	0.128	0.158	0.212	0.245
Cathay Pacific	0.174	0.071	0.091	0.179	0.137	0.14	0.208
Czech Airlines	0.06	0.182	0.064	0.127	0.254	0.197	0.117
Delta Airlines	0.13	0.134	0.077	0.124	0.108	0.266	0.16
Easyjet	0.068	0.167	0.062	0.096	0.212	0.176	0.22
Egyptian Air	0.141	0.178	0.113	0.076	0.124	0.19	0.179
Emirates	0.192	0.105	0.115	0.119	0.152	0.133	0.184
Ethiad Airways	0.152	0.098	0.13	0.154	0.152	0.122	0.192
Ethiopian Airli...	0.138	0.154	0.106	0.127	0.126	0.147	0.203

brand	In-Flight E...	Check-in P...	Customer ...	Booking a...	Refunds a...	Flight Dela...	Contact C...
Eurowings	0.064	0.233	0.049	0.124	0.124	0.202	0.203
Finnair	0.129	0.115	0.101	0.168	0.146	0.158	0.184
FlyDubai	0.151	0.145	0.127	0.159	0.172	0.133	0.115
Gulf Air	0.225	0.135	0.123	0.094	0.127	0.156	0.139
ITA Airways	0.139	0.171	0.08	0.125	0.116	0.198	0.171
Iberia	0.107	0.137	0.072	0.138	0.15	0.157	0.24
Icelandair	0.112	0.123	0.077	0.14	0.209	0.14	0.199
Indigo	0.101	0.146	0.154	0.167	0.099	0.161	0.172
Jet2	0.177	0.066	0.054	0.078	0.226	0.204	0.195
Jetblue	0.112	0.132	0.066	0.113	0.157	0.262	0.158
KLM	0.067	0.106	0.087	0.136	0.202	0.179	0.222
Kenya Airlines	0.127	0.074	0.128	0.077	0.154	0.279	0.161
Kuwait Airlines	0.123	0.146	0.145	0.083	0.143	0.197	0.163
LATAM	0.091	0.117	0.079	0.208	0.15	0.143	0.212
LEVEL	0.251	0.076	0.06	0.154	0.148	0.162	0.148
LOT Polish Airl...	0.096	0.152	0.077	0.125	0.183	0.174	0.195
Lufthansa	0.076	0.1	0.087	0.124	0.153	0.213	0.246
Malaysia Airlin...	0.118	0.071	0.115	0.168	0.17	0.149	0.21
Norse Atlantic	0.132	0.23	0.086	0.108	0.137	0.162	0.145
Norwegian	0.112	0.156	0.072	0.122	0.195	0.186	0.156
Oman Air	0.089	0.07	0.108	0.112	0.274	0.103	0.242
PLAY Airlines	0.156	0.213	0.061	0.138	0.095	0.203	0.134
Pegasus Airlin...	0.105	0.236	0.091	0.139	0.129	0.165	0.135
Philippine Airli...	0.093	0.065	0.112	0.162	0.225	0.167	0.176
Qatar	0.133	0.1	0.142	0.128	0.128	0.166	0.202
Royal Air Maroc	0.089	0.17	0.096	0.066	0.182	0.198	0.199

brand	In-Flight E...	Check-in P...	Customer ...	Booking a...	Refunds a...	Flight Dela...	Contact C...
Oman Air	0.089	0.07	0.108	0.112	0.274	0.103	0.242
PLAY Airlines	0.156	0.213	0.061	0.138	0.095	0.203	0.134
Pegasus Airlin...	0.105	0.236	0.091	0.139	0.129	0.165	0.135
Philippine Airli...	0.093	0.065	0.112	0.162	0.225	0.167	0.176
Qatar	0.133	0.1	0.142	0.128	0.128	0.166	0.202
Royal Air Maroc	0.089	0.17	0.096	0.066	0.182	0.198	0.199
Royal Jordanian	0.181	0.131	0.12	0.125	0.121	0.174	0.149
Ryanair	0.097	0.208	0.051	0.15	0.225	0.116	0.152
SAS	0.078	0.088	0.078	0.159	0.235	0.149	0.213
Scoot	0.151	0.102	0.089	0.199	0.142	0.131	0.185
Singapore Airli...	0.159	0.059	0.085	0.176	0.148	0.121	0.252
Sky Express	0.061	0.195	0.106	0.11	0.114	0.204	0.21
Srilankan Airlin...	0.146	0.07	0.212	0.08	0.152	0.119	0.221
SunExpress	0.133	0.199	0.07	0.132	0.147	0.165	0.153
TAP Air Portug...	0.064	0.122	0.065	0.126	0.217	0.171	0.234
Thai Airways	0.124	0.071	0.124	0.111	0.27	0.094	0.207
Transvia	0.069	0.235	0.083	0.128	0.165	0.161	0.159
Turkish airlines	0.094	0.125	0.111	0.167	0.131	0.182	0.19
United Airlines	0.145	0.145	0.07	0.144	0.117	0.268	0.111
Vietnam Airlines	0.13	0.099	0.091	0.161	0.185	0.107	0.225
Virgin Atlantic	0.152	0.052	0.058	0.109	0.264	0.087	0.277
Volotea	0.068	0.216	0.062	0.261	0.086	0.174	0.133
Vueling	0.066	0.173	0.057	0.116	0.15	0.208	0.229
Westjet	0.108	0.136	0.064	0.102	0.184	0.266	0.14
Wizz air	0.064	0.18	0.058	0.211	0.197	0.141	0.15
airBaltic	0.086	0.177	0.09	0.152	0.166	0.21	0.118

Table 12: Topic distribution across airlines

To give a full picture that was easier to interpret, I first made a summary in Table 13 above that showed the airline with the highest and lowest relative frequency for each of the seven dissatisfaction items.

Topic	Most frequent for	Proportion
In-Flight Experience	LEVEL	0.251
Check-in Process	Air Arabia	0.243
Customer Service & Support	Srilankan Airlines	0.212
Booking and Payment Issues	Volotea	0.261
Refunds and Compensation	Oman Air	0.274
Flight Delays and Scheduling Problems	AirSerbia	0.312
Contact and Communication Channels	AerLingus	0.292

Table 13: Airlines with the highest proportion of complaints per topic (own elaboration)

LEVEL had the most complaints concerning In-Flight Experience, which could include complaints about seat comfort, food quality, or cabin conditions. This is in accordance with the airline's low-cost, no-frills image. In the same way, Air Arabia had a lot of complaints about the Check-in

Process, especially about how they handled baggage and surprise costs, which is what you would expect from a cheap airline. Srilankan Airlines had the most unhappy customers in the Customer Service & Support category, and Volotea was the airline that got the most complaints about problems with the Booking and Payment procedure. Oman Air got the most unfavorable reviews when it came to Refunds and Compensation. This could be because their reimbursement processes are complicated or take a long time. AirSerbia, on the other hand, had the most complaints about Flight Delays and Scheduling Problems. Lastly, AerLingus had the most complaints concerning Contact and Communication Channels, which shows that it is hard for customers to reach them and get in touch with them. It's interesting that all of the airlines listed above, save for Oman Air, are either low-cost (like LEVEL, Air Arabia, and Volotea) or Value Carriers (like Srilankan, AirSerbia, and AerLingus). This pattern shows that customers in these groups may be more unhappy and frustrated, especially when service failures happen and there aren't many ways to complain, which is common in cost-conscious business models.

Topic	Least frequent for	Proportion
In-Flight Experience	Aeroitalia	0.044
Check-in Process	Air Mauritius	0.045
Customer Service & Support	Aeroitalia	0.034
Booking and Payment Issues	Royal Air Maroc	0.066
Refunds and Compensation	Volotea	0.086
Flight Delays and Scheduling Problems	Virgin Atlantic	0.087
Contact and Communication Channels	United Airlines	0.111

Table 14: Airlines with the lowest proportion of complaints per topic (own elaboration)

On the other hand, at the lower end of the displeasure scale, some carriers were seen in a better light. According to what users said, Aeroitalia had the fewest complaints about the In-Flight Experience (4.4%). This could be because the airline mostly flies short-haul, domestic flights and has only been in the market for a short time, which could affect what customers expect. Air Mauritius had the fewest problems with the Check-in process; however, this could be due to things like having fewer complicated routes or fewer passengers, much like with Aeroitalia. Aeroitalia likewise had the fewest complaints in the Customer Service & Support category, with only 3.4% of company reviews mentioning this problem. Royal Air Maroc had the fewest complaints about Booking and Payment, whereas Volotea had the fewest complaints about Refunds and Compensation. This suggests that the company's strengths and shortcomings are not in line with one another across service areas. Virgin Atlantic had the fewest complaints about flight delays and scheduling issues. Lastly, United Airlines had the fewest negative comments on Contact and Communication Channels. Most of these airlines, except for Volotea, are still classified as either value or Full-Service Network Carriers, just like in the previous analysis. This finding further supports the idea that higher service levels are usually linked to less serious complaints. This could be because the service infrastructure is stronger or the complaint resolution systems are better.

Table 12 shows the percentage of each discontent topic among the 72 airline brands in the sample. Instead of looking at each airline separately, this section gives a qualitative remark with a few examples to show how brands differ and how they are similar.

Looking at how subjects are spread out by brand shows a lot of differences. For example, ITA Airways, Italy's national airline, has the most complaints about Flight Delays and Scheduling Problems, which make up about 20% of its one-star evaluations. This means that there are problems with being on time, missing connections, or handling irregular operations. Also, two secondary drivers—Check-in and Airport Process and Contact and Communication—are tied at about 17.1%, which shows that a lot of people are unhappy with both the pre-boarding phase and the post-service customer engagement. Complaints about the In-Flight Experience (13.9%) and problems with booking and payment (12.5%) are also significant, while complaints about customer service and support (8.0%) and refunds and compensation (11.6%) are smaller, suggesting that structural inefficiencies may be more important than interpersonal interactions in causing customer frustration.

Ryanair, on the other hand, has a very distinct pattern, with most of its complaints coming from procedural and transactional areas. Refunds and Compensation is the most common complaint, making up 22.5% of all complaints. Check-in and Airport Process is next, with 20.8%. These results show that people often complain about the airline's tight luggage and refund procedures, which fit with its philosophy of being low-cost and efficient. Complaints regarding Contact and Communication (15.2%) and Booking and Payment Issues (14.9%) back up the idea that travelers think the support system and booking process aren't very good. On the other hand, Flight Delays and In-Flight Experience get less attention (11.6% and 9.7%, respectively), which could be because passengers don't expect much in these areas. Customer Service & Support only makes up 5.1% of the total, which suggests that the problems people see are more related to how the system works than how the staff acts.

Qatar Airways has a very even distribution of complaints among full-service airlines, with Contact and Communication being the most common (20.1%). This signals that it may not be very attentive or helpful after the trip, even though it is in the premium market. Complaints about flight delays (16.6%), customer service and support (14.2%), and booking and payment problems (12.8%) also show that the company has trouble keeping its operations and services consistent. There are some complaints about the In-Flight Experience (13.3%), but they aren't very serious. This could be because the airline focuses on cabin service. Still, the fact that there are several moderate dissatisfaction drivers shows that there may be a gap between what the brand promises and what it actually delivers.

When it comes to Norwegian, the most talked-about topic is Refunds and Compensation (19.5%), followed closely by Flight Delays (18.6%) and Check-in and Communication Problems (15.6% apiece). This trend shows that the airline is still having trouble dealing with disruptions and keeping operations running smoothly. This could be because the airline uses a hybrid low-cost/long-haul business. Even while In-Flight Experience (11.1%) and Customer Service (7.2%) are less common complaints, the fact that they are spread out across the full customer experience implies that there are problems with the system as a whole.

Lastly, Etihad Airways, another full-service international airline, has a wide range of complaints. Contact and Communication is once again in the lead at 19.2%, followed by Booking and Payment Issues (15.4%), Refunds and Compensation (15.2%), and In-Flight Experience (15.2%). These numbers show that people are unhappy at more than one point in their travel, from booking until after the flight. There were fewer complaints about Check-in (9.8%) and Delays (12.2%), which means that operational reliability and ground handling are getting better. However, there are still problems with digital and transactional areas.

These examples show that even though the companies are in the same industry and serve similar consumers, the reasons for customer discontent are very different for each company. People who fly with low-cost airlines like Ryanair tend to complain more about refund policies and strict procedures. On the other hand, full-service airlines like Qatar and Etihad get a wider range of complaints, often because customers have higher expectations. To understand the specific problems that passengers face and to come up with personalized plans to improve service and win back customer trust, these qualitative differences are highly important.

3.3.1 Analysis of ANOVA and Post-Hoc Bonferroni Comparisons

Following the in-depth analysis of dissatisfaction topics at the brand level, this section addresses the second research question: *What differences, if any, exist in the nature and frequency of dissatisfaction across Full-Service, Low-Cost, and Value carrier categories? Are there any common themes that transcend these classifications?*

The first step in the analysis was to produce an Excel file that showed how each airline fit into one of the three groups, as shown in Table 11 of the preceding paragraph. Then, this file was brought into KNIME and combined with the topic modeling output using the Joiner node. The crucial variable was the airline name ("brand"). At this point, it was very important to make sure that the airline names in all datasets were exactly the same - even small differences would have made it impossible to link them correctly. I looked over and fixed any mistakes in naming by hand before moving on. After the merge was done, the combined dataset was sent out through the Excel Writer node and then looked at in SPSS. The statistical study employed the airline category as an independent variable and the seven topic proportions as dependent variables. Next, descriptive statistics were used to find out how the seven discontent concerns are spread out throughout the three types of airline businesses: Full-Service Network Carriers (FSCs), Low-Cost Carriers (LCCs), and Value Carriers (VCs). The tables below (15 and 16) show the average subject proportion for each group and give a first idea of how important each sort of complaint is in each category.

These descriptive means, which were calculated using both SPSS (Table 16) and KNIME (Table 15), show the average number of reviews for each topic for each type of airline. A higher mean means that the item is brought up more often as a reason for dissatisfaction in that category, which gives us a useful way to look at passenger concerns in comparison to other categories.

Classification String	In-Flight Experience Number (double)	Check-in Process Number (double)	Customer Service ... Number (double)	Booking and Paym... Number (double)	Refunds and Com... Number (double)	Flight Delays and ... Number (double)	Contact Channels Number (double)
Full-Service Network C...	0.126	0.095	0.091	0.122	0.165	0.168	0.233
Low-Cost Carrier	0.093	0.174	0.061	0.139	0.195	0.159	0.179
Value Carrier	0.114	0.129	0.083	0.123	0.16	0.193	0.198

Table 15: Average topic proportions by airline category

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
In-Flight Experience	Full-Service Network Carrier	25398	,125613064	,228853461	,001436011	,122798401	,128427727	,000274364	,986483880
	Low-Cost Carrier	41647	,093346398	,190615620	,000934042	,091515656	,095177140	,000264678	,991781128
	Value Carrier	15278	,114000801	,215961536	,001747202	,110576076	,117425525	,000332087	,992347044
	Total	82323	,107134364	,208337286	,000726117	,105711181	,108557547	,000264678	,992347044
Check-in Process	Full-Service Network Carrier	25398	,095252889	,171512213	,001076206	,093143465	,097362314	,000301182	,983422645
	Low-Cost Carrier	41647	,174150450	,255596296	,001252457	,171695610	,176605291	,000344810	,992183984
	Value Carrier	15278	,129491617	,208309815	,001685297	,126188234	,132795000	,000470379	,981714561
	Total	82323	,141521198	,226723344	,000790197	,139972418	,143069979	,000301182	,992183984
Customer Service & Support	Full-Service Network Carrier	25398	,091491028	,163904870	,001028471	,089475166	,093506889	,000250273	,994102011
	Low-Cost Carrier	41647	,060878614	,131947140	,000646559	,059611345	,062145882	,000276869	,984689815
	Value Carrier	15278	,082653377	,158127837	,001279308	,080145780	,085160973	,000356172	,994787086
	Total	82323	,074364139	,148091461	,000516142	,073352504	,075375774	,000250273	,994787086
Booking and Payment Issues	Full-Service Network Carrier	25398	,122275532	,194109511	,001217999	,119888184	,124662880	,000193266	,977509503
	Low-Cost Carrier	41647	,139157521	,214952538	,001053297	,137093038	,141222004	,000350044	,986592970
	Value Carrier	15278	,122678466	,195268246	,001579786	,119581897	,125775036	,000300859	,974921288
	Total	82323	,130890867	,205291456	,000715501	,129488490	,132293243	,000193266	,986592970
Refunds and Compensation	Full-Service Network Carrier	25398	,165007148	,229380922	,001439321	,162185998	,167828298	,000482072	,984933829
	Low-Cost Carrier	41647	,194553456	,254566752	,001247412	,192108503	,196998408	,000452144	,991209689
	Value Carrier	15278	,160358896	,230820259	,001867414	,156698541	,164019250	,000419181	,985577395
	Total	82323	,179091900	,243209059	,000847655	,177430503	,180753298	,000419181	,991209689
Flight Delays and Scheduling Problems	Full-Service Network Carrier	25398	,167777165	,233131852	,001462857	,164909882	,170644448	,000559805	,984469138
	Low-Cost Carrier	41647	,158646749	,234470161	,001148936	,156394812	,160898687	,000362603	,987641314
	Value Carrier	15278	,192548434	,251268007	,002032843	,188563818	,196533049	,000389039	,990496004
	Total	82323	,167755312	,237596492	,000828094	,166132255	,169378369	,000362603	,990496004
Contact Channels	Full-Service Network Carrier	25398	,232583174	,266554530	,001672578	,229304826	,235861521	,000379675	,985934913
	Low-Cost Carrier	41647	,179266812	,245148440	,001201261	,176912317	,181621308	,000580198	,986711392
	Value Carrier	15278	,198268410	,248116610	,002007348	,194333769	,202203051	,000797373	,984642528
	Total	82323	,199242218	,253559178	,000883728	,197510118	,200974319	,000379675	,986711392

Table 16: Descriptive statistics from SPSS for dissatisfaction topic proportions by airline category

There is a clear difference in the findings across the three groups. The first issue, In-Flight Experience, is the most common among Full-Service Network Carriers (Mean = 0.126), followed by Value (0.114) and Low-Cost (0.093). This pattern shows that FSCs passengers may have higher expectations for seat comfort, food on board, or staff professionalism—areas where perceived shortcomings might make people even more unhappy. Second, Low-Cost Carriers had the most complaints about the Check-in Process (0.174), which is far higher than Value Carriers (0.129) and Full-Service (0.095). This shows that check-in procedures, which frequently include strict baggage limits, less people at the counter, and less flexibility, are a major source of problems in the low-cost market. Customer Service & Support also has the highest mean in the Full-Service category (0.091), followed by Value (0.083) and Low-Cost (0.061). This shows that there may be a difference between what people expect from personalized treatment and what full-service airlines actually provide. On the other hand, LCCs passengers may expect little engagement and hence complain less in this area. Next, Booking and Payment Issues are most common among Low-Cost Carriers (0.139), followed closely by Value (0.123) and Full-Service Network Carriers (0.122). These results are in line with what people already know about low-cost booking experiences, which often have hidden costs, upselling, and a lack of price transparency. Refunds and Compensation is a big problem for Low-Cost Carriers (0.195), more than for Full-Service (0.165) and Value Carriers (0.160). This makes people think that refund processes in the low-cost industry are generally strict, slow, or unclear, which makes customers very angry. Also, Flight Delays and Scheduling Problems show a different pattern: Value Carriers have the highest mean (0.193), followed closely by Full-Service (0.168) and Low-Cost (0.159). This shows that operational volatility may have a bigger impact on mid-tier airlines than on other types of airlines. This could be because they have fewer resources or a smaller network of routes. Last but not least, Full-Service Network Carriers have the most Contact and Communication Channels (0.233), followed by Value (0.198) and Low-Cost (0.179). This may seem strange, but it is probably because customers want full-service settings to offer real-time, multi-channel help. When these expectations aren't realized, they become quite unhappy.

These descriptive results already point to a varied pattern of complaints for each type of airline. But to check if these differences are statistically significant, a one-way ANOVA was run for each issue. The one-way ANOVA analysis findings, which are provided in Table 17 below, show that the differences in mean topic proportions between airline categories are statistically significant for all seven topics. The p-values are less than .001 and the F-values are always high. These results strongly suggest that the sort of complaints passengers are most likely to make is greatly affected by the airline's business strategy, whether it is full-service, low-cost, or value oriented. In this way, the reasons why customers are unhappy are not the same across the board; they depend on the operational and service features of each type of airline. This result clearly answers the second research question of this thesis: the type of airline is a major factor in what service components get bad reviews.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
In-Flight Experience	Between Groups	17,310	2	8,655	200,372	<,001
	Within Groups	3555,829	82320	,043		
	Total	3573,139	82322			
Check-in Process	Between Groups	100,922	2	50,461	1005,625	<,001
	Within Groups	4130,715	82320	,050		
	Total	4231,637	82322			
Customer Service & Support	Between Groups	16,074	2	8,037	369,742	<,001
	Within Groups	1789,337	82320	,022		
	Total	1805,410	82322			
Booking and Payment Issues	Between Groups	5,762	2	2,881	68,467	<,001
	Within Groups	3463,665	82320	,042		
	Total	3469,426	82322			
Refunds and Compensation	Between Groups	20,356	2	10,178	172,787	<,001
	Within Groups	4849,043	82320	,059		
	Total	4869,399	82322			
Flight Delays and Scheduling Problems	Between Groups	12,847	2	6,423	114,096	<,001
	Within Groups	4634,403	82320	,056		
	Total	4647,249	82322			
Contact Channels	Between Groups	44,865	2	22,433	351,891	<,001
	Within Groups	5247,802	82320	,064		
	Total	5292,667	82322			

Table 17: ANOVA results for topic proportions by airline classification

Some of the seven topics show quite large variations between groups. The Check-in Process subject had the highest F-value (F = 1005.63), which means that complaints varied a lot amongst different types of airlines. Customer Service & Support (F = 369.74) and Contact and Communication Channels (F = 351.89) come next. It looks like these three service areas are very sensitive to changes in how a business is set up and how resources are used. For instance, low-cost airlines that use leaner, digital-first systems may have fewer places for passengers to interact with staff in person and more strict check-in procedures, which might make things harder for passengers. Decentralized or automated customer service systems may also make people more unhappy with how easy it is to get in touch and how quickly they respond. The fact that the statistical significance is the same for all themes shows that airline segmentation is useful for understanding how passengers feel. It also sets the stage for more targeted service improvements that are specific to each business model.

ANOVA results showed that the overall differences in dissatisfaction topics between airline categories are statistically significant, but they don't show which pairings of categories are different from one another. Bonferroni post-hoc tests were done for each issue after the ANOVA to deal with this. These tests let you compare Full-Service, Value, and Low-Cost Carriers with each other while correcting for the higher chance of Type I error that comes with doing many comparisons. Appendix

A has the full results of these tests. As expected, almost all pairwise differences are statistically significant, which shows that differences in business models have a consistent effect on the types of complaints.

The ANOVA indicated a big difference between airline groups for In-Flight Experience ($F = 200.372$, $p < .001$), and the Bonferroni test shows that all pairwise differences are statistically significant ($p < .001$). Full-Service Network Carriers had the highest mean ($M = 0.126$), followed by Value (0.114) and Low-Cost Carriers (0.093). This shows that passengers flying with full-service airlines are more unhappy with their In-Flight Experience, probably because they have higher expectations for seat comfort, food, entertainment, and crew service. This group may be more likely to criticize even small mistakes harshly because these brands work hard to maintain a high-end image.

Low-Cost Carriers, on the other hand, have the highest mean ($M = 0.174$) for the Check-in Process, followed by Value (0.129) and Full-Service Network Carriers (0.095). The ANOVA showed that this difference was very important ($F = 1005.625$, $p < .001$), and the Bonferroni test confirmed that all pairwise comparisons were also important. This supports the concept that check-in and airport-related procedures are a big problem for low-cost travelers, probably because of self-service technology, severe baggage rules, and not enough physical assistance people.

The test showed big differences for Customer Service and Support ($F = 369.742$, $p < .001$), and all pairwise comparisons are statistically significant. Once more, Full-Service Network Carriers have the highest mean ($M = 0.091$), followed by Value (0.083) and Low-Cost Carriers (0.061). This means that those who fly with full-service airlines are more likely to say they are unhappy with the customer service. This could be because they want greater attention and individualized care. On the other hand, those who fly on low-cost airlines may have lesser expectations to begin with, which means they don't complain as much about this area.

In the fourth issue, Booking and Payment Issues, the ANOVA result is significant ($F = 68.467$, $p < .001$), but the difference between Full-Service and Value Carriers is not statistically significant ($p = 1.000$). However, both groups are considerably different from Low-Cost Carriers ($p < .001$). This finding shows that problems with booking, like hidden fees, upselling, or unclear pricing, happen more often in the low-cost segment. At the same time, the fact that FSCs and VCs are similar in this area suggests that their booking processes may be easier to use and more predictable.

There was also a big influence on the Refunds and Compensation topic ($F = 172.787$, $p <.001$), but once again, the difference between Full-Service and Value Carriers is not big enough ($p =.184$).

Low-Cost Carriers are still the most unhappy (M = 0.195), followed by Full-Service (0.165) and Value Carriers (0.160). This shows that refund and compensation procedures are a common problem in the low-cost sector, where they are commonly seen as unclear, slow, or too strict. Value and Full-business carriers may have similar problems with addressing post-transaction compensation claims, even if their business models are different. This is because both types of carriers have about the same level of customer dissatisfaction. This overlap also makes the suggested Value Carrier category more believable by showing that these airlines are very different from Low-Cost Carriers and, in some ways, more similar to Full-Service operations.

Also, for the sixth topic about Flight Delays and Scheduling Problems, the ANOVA shows that there is a big difference between airline types (F = 114.096, $p < .001$). Value Carriers have the highest mean (M = 0.193), which is much higher than both Full-Service (0.168) and Low-Cost Carriers (0.159). This suggests that operational reliability is a major weakness in the mid-tier segment. These carriers might not have the backup and logistical support that full-service airlines do, and they might fly more complicated and varied routes than normal low-cost models, which makes them more vulnerable to problems.

The last issue, Contact and Communication Channels, likewise has a very big difference (F = 351.891, $p < .001$), and all pairwise comparisons are also significant. Full-Service Network Carriers had the highest average (M = 0.233), followed by Value (0.198) and Low-Cost Carriers (0.179). At first, this result was startling, but it shows that full-service passengers have very high expectations for quick, multi-channel communication. When responses are slow, automatic, or lack empathy, customers are even more unhappy, especially when these airlines push a high touch image.

In short, the Bonferroni post-hoc results strongly support the idea that airline business strategies affect not only how often customers are unhappy, but also the kinds of things that make them unhappy. The differences between the groups are both statistically and practically significant, which supports the segmentation used in this study and gives useful information for making service enhancements that are specific to each group.

Chapter 4: General discussion

4.1 Theoretical contributions

This thesis adds to the growing academic conversation regarding electronic word-of-mouth (eWOM), service quality, and customer trust by looking at a topic that hasn't been examined much before: one-star airline reviews on Trustpilot in the European market. I learned more about what makes customers unhappy in the airline sector by putting together diverse theories, like cognitive dissonance theory and signaling theory.

The study looks at the most emotionally charged and diagnostically rich user feedback by only looking at one-star reviews. There has been a lot of research on the general effects of eWOM (Litvin et al., 2008; Jalilvand & Samiei, 2012), but there hasn't been as much research on the specific effects of negative eWOM (NWOM), especially in its most extreme form. This research fills in that gap by showing that extreme reviews not only have different tones, but also different thematic structures. It does this by using Latent Dirichlet Allocation (LDA) to find seven different complaint categories: In-Flight Experience, Check-in Process, Customer Service & Support, Booking and Payment Issues, Refunds and Compensation, Flight Delays and Scheduling Problems, and Contact and Communication Channels. This thematization adds to theoretical frameworks on service quality by showing how concerns have changed from product-related issues (like seat comfort) to process- and interaction-related issues (such as how easy it is to get support and how reliable the schedule is). The fact that there are relatively few complaints about in-flight treatment (10.9%) and customer service (5.6%) shows that problems with the purchasing process and after the purchase may be more important in making customers unhappy than what has been said in the past. These include challenges with communication, disagreements about refunds, and scheduling concerns, all of which show that there are common service problems.

This thematic structuring adds complexity to Expectation Confirmation Theory (Oliver, 1980) by showing how big differences between expected and actual service delivery can lead to responses that are far worse than they should be. In the ANOVA study, Full-Service Network Carriers (FSCs) had the greatest average levels of discontent in three areas: In-Flight Experience, Customer Service & Support, and Contact and Communication Channels. This pattern fits with the premise that the more a brand is seen and positioned as premium, the greater the expectations it generates. When these high expectations aren't realized, people tend to express their disappointment more strongly.

This thesis also makes a big contribution by introducing a three-part taxonomy of airline business models: Full-Service Network Carriers (FSCs), Low-Cost Carriers (LCCs), and Value Carriers (VCs). This segmentation moves the theoretical conversation about how to differentiate markets forward by recognizing that there are hybrid models that don't fit neatly into standard categories. The data, backed up by ANOVA and Bonferroni testing, demonstrates that the themes of consumer expectations and discontent are different in these groups, not just because of price but also because of how they think the service will be delivered and what it would be like. This means that we need to think about how we show airline categories in models of consumer response and service evaluation again.

The work also adds to the rising use of unsupervised machine learning methods in marketing and consumer behavior research. Using Latent Dirichlet Allocation (LDA) to look at almost 100,000 reviews shows that it can find hidden trends without having to utilize pre-set coding systems. Finding seven semantically different categories, such as booking problems and In-Flight Experiences, is a scalable and repeatable way to look at vast amounts of text data. LDA is not a new method in academic research (Blei et al., 2003; Hu et al., 2018) but using it specifically on one-star airline reviews gives it a fresh context that supports its theoretical usefulness in analyzing service-related complaints.

Finally, the study shows how important platform-specific dynamics are in determining how consumer feedback is made and understood. Some people dispute Trustpilot's open-access approach because it makes it easier for phony reviews to get through, but it also lets people express their feelings about customers in a more honest and intense way. This part should be added to future theoretical models of eWOM credibility, source trustworthiness, and platform-mediated brand perception (Flanagin & Metzger, 2013; Kirilenko et al., 2024).

All of these contributions improve existing theoretical frameworks and create new opportunities for future research into how the interaction between consumers, digital platforms, and service-based enterprises is changing.

4.2 Managerial implications

The findings of this study offer several significant implications for airline managers, especially when it comes to designing services, managing expectations, taking care of customers, and keeping an eye on their internet reputation. By using Latent Dirichlet Allocation (LDA) on a huge set of one-star reviews and finding seven main reasons why customers were unhappy, I was able to show that there were common operational problems that, if addressed, may lead to better, evidence-based management solutions.

First, the fact that communication-related issues made up 21.0% of all complaints shows how important it is to have responsive, multichannel, and well-staffed customer care systems. Not getting back to emails, call centers that aren't helpful, or slow responses after a purchase have become the most common cause of disappointment. This means that communication should no longer be seen as an extra service, but as an important part of the customer experience. Making sure that passengers can immediately get in touch with support services and get clear, caring answers could help reduce discontent, especially when there are problems with service or delays.

Second, the statistics show that there is a clear gap between what customers expect and what they really get from full-service airlines. Full-Service Network Carriers (FSCs), like Qatar, had the most unhappy customers when it came to things like the In-Flight Experience, customer service and support, and ways to get in touch with them. This shows that high expectations, which are caused by branding and service positioning, may make people more disappointed when the experience doesn't live up to the promise. For these carriers, it is very important to either make sure that service is consistent at all key touchpoints or to change what customers expect through clearer and more accurate marketing messaging.

Third, the data shows that Low-Cost Carriers (LCCs) have a long-standing problem with their refund and compensation processes. Complaints in this area made up 18.2% of all one-star evaluations and were more common with LCCs than with other types of companies. This data shows that these carriers need to take a hard look at how easy it is to understand, how fast it is, and how clear their reimbursement procedures are. Making digital refund processes easier and policies clearer could make customers feel much better about their experiences, especially when their bags are misplaced, their flights are delayed, or their flights are canceled. These are times when customers typically feel powerless.

Fourth, the empirical introduction of the value carrier segment has shown how weak hybrid business models can be when it comes to strategy. Value Carriers are stuck between full-service and low-cost models. They seem to have trouble meeting high consumer expectations because they don't have the infrastructure to do so all the time, especially when it comes to flight delays and scheduling issues. This means that the mid-market positioning could confuse or upset customers if it isn't backed up with a clear value proposition and a few well-done service elements. Investing more in certain service aspects, such as more flexible policies or a better boarding experience, could help align passenger expectations and lower discontent in this group.

Finally, the results show how important open-access review sites like Trustpilot are becoming for altering how people see brands and how much they trust them. Skytrax has been used more often in past academic studies, but Trustpilot is a great tool for keeping track of how people feel about a product because it is big, easy to use, and always trying to make itself more trustworthy by finding fraud automatically. When people leave unsolicited, emotionally charged criticism on these kinds of sites, airlines may find out about problems early and deal with unhappy passengers right away. My recommendation would be to set up specific steps for keeping track of, assessing, and responding to reviews on these sites that can not only help with individual complaints, but it might also show the public that the organization is responsive and honest.

Overall, this study gives managers useful information that can help them make better, more focused decisions for different types of airline businesses. Airlines can move toward a more responsive and strategically aligned approach to customer experience management by concentrating on the specific dissatisfaction themes that matter most to passengers and recognizing that these themes change depending on the kind of carrier.

4.3 Limitations and areas for further research

While this thesis offers valuable insights into extreme consumer dissatisfaction in the European airline sector, several limitations constrain the scope and generalizability of the findings.

First, focusing only on one-star reviews, even though it was planned and based on theory, limits the variety of emotions that can be investigated. The analysis can't distinguish the difference between minor unhappiness and deep-seated frustration because it doesn't look at reviews that are neutral or positive. In the future, researchers might utilize comparative topic modeling at all levels of satisfaction to learn more about how feelings spread and how topics differ amongst satisfaction groups.

Second, the dataset might be affected by survivorship bias and self-selection effects. The sample only includes people who chose to leave a review, which is usually because they had a strong emotional experience. Passengers who had bad experiences but chose not to leave feedback are automatically left out. This makes it more likely that people who are very involved (and often unhappy) will use it. Future research should make it clear that this kind of data is self-referential and think about adding other sources, like structured consumer surveys or statistics on how complaints are handled, to confirm and put review-based findings in context.

Third, Latent Dirichlet Allocation (LDA) is a powerful and scalable approach to locate subjects, but it only works on the *bag-of-words* model, which doesn't take into consideration the sequence of words or the context. This makes it tougher for the model to properly understand what things mean, irony, or how things are connected. More complex natural language processing (NLP) methods, such as BERT or transformer-based sentiment analysis models, might be better at putting user comments in context and making it easier to interpret.

Fourth, the classification of airlines, notably the new value carrier group, was based on a qualitative assessment of information that was already available to the public. This strategy did allow for more meaningful segmentation than just full-service and Low-Cost Carriers, although it is still a little subjective. Adding survey data that illustrates how people feel about different types of airlines to this classification could make it more valid.

Fifth, the study only looked at reviews that were written in English. This language barrier may have precluded a lot of good customer feedback from being incorporated because the European aviation market is multilingual. Adding reviews in more than one language would make the analysis more culturally inclusive and give us more information about what people in different regions expect and are unhappy about.

Sixth, fake or dishonest reviews could affect the general impression of what people are dissatisfied about. Even while sites like Trustpilot have improved their detection systems better and better, removing nearly 4.5 million false reviews in 2024 alone, there is still a potential that the sample may have been corrupted by bad reviews generated by bots or competitors. In the future, it may be possible to compare the content of evaluations with objective performance statistics, such as the number of flight delays, the time it takes to resolve complaints, or the layout of the seats. This might help in figuring out what people truly think and separating real customer experiences from fake ones.

Finally, this study solely looked at the European market but employing the same methodology in places like North America or Asia-Pacific could let us compare regions in a relevant way. These kinds of comparisons might help in figuring out if the patterns of unhappiness identified here are the same everywhere or if they change depending on where you are.

Future research should not just look for similar themes of unhappiness, but also how these topics affect people's behavior. For example, researchers could look at how some complaints affect things like consumers canceling their reservations, being less ready to pay, or hurting brand trust and the company's image. Understanding these consequences on behavior will help airline service managers and brand strategists make better decisions.

It might also be useful to learn more about how customers issues vary over time by adding dynamic topic modeling. By looking at how review themes change over time, researchers can uncover new problems and see how well efforts to make customers happier are working.

Another option could be to combine different types of data, like social media posts, customer service interactions, and complaint logs, to get a better picture of how unhappy customers are. Mixing textual analysis with other kinds of data might show patterns that aren't clear in review texts by themselves.

Additionally, learning more about how cultural variations affect what customers expect and how they see things could help to better understand why they are upset. Cross-cultural studies could illustrate how cultural norms and values shape how people think about service quality and how likely they are to complain about it in public.

In the end, figuring out how well airlines respond to bad reviews could help them figure out the best ways to deal with customers and manage their reputations. Airlines may be able to deal with unhappy customers better if they look at how their response strategies affect how customers see them.

Scholars and practitioners can learn more about why customers are unhappy with airlines and come up with better ways to improve customer experience and loyalty by addressing these limitations and following the suggested paths for future research.

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Appendix A

Multiple Comparisons

Bonferroni

Dependent Variable	(I) class	(J) class	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
In-Flight Experience	Full-Service Network Carrier	Low-Cost Carrier	,032266666*	,001654662	<,001	,028305358	,036227974
		Value Carrier	,011612264*	,002127913	<,001	,006517979	,016706548
	Low-Cost Carrier	Full-Service Network Carrier	-,03226667*	,001654662	<,001	-,036227974	-,028305358
		Value Carrier	-,02065440*	,001965822	<,001	-,025360636	-,015948169
	Value Carrier	Full-Service Network Carrier	-,01161226*	,002127913	<,001	-,016706548	-,006517979
		Low-Cost Carrier	,020654402*	,001965822	<,001	,015948169	,025360636
Check-in Process	Full-Service Network Carrier	Low-Cost Carrier	-,07889756*	,001783411	<,001	-,083167098	-,074628024
		Value Carrier	-,03423873*	,002293486	<,001	-,039729398	-,028748057
	Low-Cost Carrier	Full-Service Network Carrier	,078897561*	,001783411	<,001	,074628024	,083167098
		Value Carrier	,044658833*	,002118782	<,001	,039586408	,049731259
	Value Carrier	Full-Service Network Carrier	,034238728*	,002293486	<,001	,028748057	,039729398
		Low-Cost Carrier	-,04465883*	,002118782	<,001	-,049731259	-,039586408
Customer Service & Support	Full-Service Network Carrier	Low-Cost Carrier	,030612414*	,001173775	<,001	,027802363	,033422465
		Value Carrier	,008837651*	,001509487	<,001	,005223895	,012451407
	Low-Cost Carrier	Full-Service Network Carrier	-,03061241*	,001173775	<,001	-,033422465	-,027802363
		Value Carrier	-,02177476*	,001394504	<,001	-,025113245	-,018436281
	Value Carrier	Full-Service Network Carrier	-,00883765*	,001509487	<,001	-,012451407	-,005223895
		Low-Cost Carrier	,021774763*	,001394504	<,001	,018436281	,025113245
Booking and Payment Issues	Full-Service Network Carrier	Low-Cost Carrier	-,01688199*	,001633078	<,001	-,020791623	-,012972355
		Value Carrier	-,000402935	,002100155	1,000	-,005430766	,004624896
	Low-Cost Carrier	Full-Service Network Carrier	,016881989*	,001633078	<,001	,012972355	,020791623
		Value Carrier	,016479054*	,001940178	<,001	,011834212	,021123896
	Value Carrier	Full-Service Network Carrier	,000402935	,002100155	1,000	-,004624896	,005430766
		Low-Cost Carrier	-,01647905*	,001940178	<,001	-,021123896	-,011834212

Dependent Variable	(I) class	(J) class	Mean Difference (I–J)	Std. Error	Sig.	Lower Bound	Upper Bound
Booking and Payment Issues	Full-Service Network Carrier	Low-Cost Carrier	-,01688199*	,001633078	<,001	-,020791623	-,012972355
		Value Carrier	-,000402935	,002100155	1,000	-,005430766	,004624896
	Low-Cost Carrier	Full-Service Network Carrier	,016881989*	,001633078	<,001	,012972355	,020791623
		Value Carrier	,016479054*	,001940178	<,001	,011834212	,021123896
	Value Carrier	Full-Service Network Carrier	,000402935	,002100155	1,000	-,004624896	,005430766
		Low-Cost Carrier	-,01647905*	,001940178	<,001	-,021123896	-,011834212

Dependent Variable	(I) class	(J) class	Mean Difference (I–J)	Std. Error	Sig.	Lower Bound	Upper Bound
Refunds and Compensation	Full-Service Network Carrier	Low-Cost Carrier	-,02954631*	,001932266	<,001	-,034172207	-,024920407
		Value Carrier	,004648253	,002484915	,184	-,001300704	,010597209
	Low-Cost Carrier	Full-Service Network Carrier	,029546307*	,001932266	<,001	,024920407	,034172207
		Value Carrier	,034194560*	,002295629	<,001	,028698758	,039690362
	Value Carrier	Full-Service Network Carrier	-,004648253	,002484915	,184	-,010597209	,001300704
		Low-Cost Carrier	-,03419456*	,002295629	<,001	-,039690362	-,028698758
Flight Delays and Scheduling Problems	Full-Service Network Carrier	Low-Cost Carrier	,009130416*	,001889017	<,001	,004608056	,013652775
		Value Carrier	-,02477127*	,002429295	<,001	-,030587071	-,018955467
	Low-Cost Carrier	Full-Service Network Carrier	-,00913042*	,001889017	<,001	-,013652775	-,004608056
		Value Carrier	-,03390168*	,002244247	<,001	-,039274475	-,028528894
	Value Carrier	Full-Service Network Carrier	,024771269*	,002429295	<,001	,018955467	,030587071
		Low-Cost Carrier	,033901684*	,002244247	<,001	,028528894	,039274475
Contact Channels	Full-Service Network Carrier	Low-Cost Carrier	,053316362*	,002010146	<,001	,048504015	,058128708
		Value Carrier	,034314764*	,002585069	<,001	,028126035	,040503493
	Low-Cost Carrier	Full-Service Network Carrier	-,05331636*	,002010146	<,001	-,058128708	-,048504015
		Value Carrier	-,01900160*	,002388155	<,001	-,024718908	-,013284288
	Value Carrier	Full-Service Network Carrier	-,03431476*	,002585069	<,001	-,040503493	-,028126035
		Low-Cost Carrier	,019001598*	,002388155	<,001	,013284288	,024718908

*. The mean difference is significant at the 0.05 level.