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Research Article

Uncovering airline service quality dimensions from passengers' online reviews: A text mining approach to validate and extend Servqual[1]

Yolcuların çevrimiçi incelemelerinden havayolu hizmet kalitesi boyutlarının belirlenmesi: Servqual'i doğrulamak ve genişletmek için metin madenciliği yaklaşımı

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Abstract

This study investigates airline service quality dimensions by employing text-mining techniques to analyse passengers' emotional responses and experiences with airlines as reflected in their online reviews. The study aims to identify the relationship between these and SERVQUAL dimensions to confirm its reliability in the airline industry and reveal new and promising dimensions of airline service quality. The study contributes to academia by enriching literature on airline service quality and text mining applications, identifying areas for enhancement, and suggesting strategic directions for continuous improvement to practitioners based on passengers' quality perceptions of airline service experiences. With a large dataset from 100 airlines obtained from Skytrax, the study offers a deeper understanding of airline service quality. It encourages using big data and text-mining techniques to explore consumer preferences. The study's findings challenge traditional models and bring out new, context-specific service quality characteristics to provide a greater understanding of passenger experiences. These give the airlines insightful guidance on improving service offerings and fulfilling customer expectations, eventually improving customer satisfaction, loyalty, and competitive positioning.

Keywords: Text-Mining, Topic Modelling, Sentiment Analysis, Skytrax; Online Customer Reviews

Jel Codes: M30, M31, C88

Öz

Bu çalışma, havayolu hizmet kalitesi boyutlarını, yolcuların çevrimiçi yorumlarında yansıtılan havayollarına yönelik duygusal tepkilerini ve deneyimlerini analiz etmek için metin madenciliği tekniklerini kullanarak incelemektedir. Çalışma, bu boyutlar ile SERVQUAL boyutları arasındaki ilişkiyi belirleyerek havayolu endüstrisindeki SERVQUAL boyutlarının güvenilirliğini doğrulamayı ve havayolu hizmet kalitesi üzerine yeni ve umut verici boyutları ortaya çıkarmayı amaçlamaktadır. Araştırma, yalnızca havayolu hizmet kalitesi ve metin madenciliği uygulamaları üzerine literatürü zenginleştirerek akademiye katkıda bulunmakla kalmayıp, aynı zamanda geliştirilmesi gereken alanları belirlemekte ve yolcuların havayolu hizmet deneyimlerine ilişkin kalite algılarına dayanarak uygulayıcılara sürekli iyileştirme için stratejik yönler önermektedir. Skytrax'tan elde edilen 100 havayoluna ait geniş bir veri setiyle çalışma, havayolu hizmet kalitesi hakkında daha derin bir anlayış sunmakta ve tüketici tercihlerini keşfetmede büyük veri ve metin madenciliği tekniklerinin kullanımını teşvik etmektedir. Çalışmanın bulguları, geleneksel modellere meydan okumakta ve yolcu deneyimlerinin daha iyi anlaşılmasını sağlamak için hizmet kalitesinin yeni, bağlama özgü özelliklerini ortaya çıkarmaktadır. Bu bulgular, havayollarına hizmet sunumlarını nasıl iyileştirebilecekleri ve müşteri beklentilerini nasıl daha iyi karşılayabilecekleri konusunda içgörü sağlayan bir rehberlik sunmakta, bu da nihayetinde müşteri memnuniyetini, sadakatini ve rekabet konumunu iyileştirecektir.

Anahtar Kelimeler: Metin Madenciliği, Konu Modelleme, Duygu Analizi, Skytrax, Çevrimiçi Müşteri Değerlendirmeleri

JEL Kodları: M30, M31, C88

Introduction

As a concept that compares the perceived expectations of customers and the perceived performance of a service, service quality is a critical factor that affects consumer satisfaction, customer loyalty and overall organisational success (Ding et al., 2020). The definition, scope and sub-dimensions of this concept have been the focus of many researchers and practitioners. Since the concept's significance and influence on service experiences have become more apparent, the need for accurate measurement has become undeniably necessary (Zeithaml et al., 1993); as a result, different measurements, especially survey-based tools, were proposed. SERVQUAL, which has tangibility, reliability, responsiveness, assurance, and empathy as dimensions, is widely recognised as the most accepted measurement approach among these. The primary purpose of the emergence and use of this generic measuring instrument is to understand the relationship between customer expectations and their actual perceptions of service (Parasuraman et al., 1988), and it is used in different industries like banking (Aghdaie and Faghani 2012; Yesmin et al., 2023), hospitality (Jacob et al., 2022), retail (Haming et al., 2019), education (Udo et al., 2011).

In today's competitive global market, service quality has also emerged as a significant factor for airlines due to its numerous benefits, including enhancing competitiveness, fostering customer loyalty, and increasing market share (Gupta, 2018). Hence, scholars and practitioners have focused on evaluating airline service quality in the airline industry. For instance, prior studies like Tsaur et al. (2002), Park et al. (2006), more recent ones like Tahanisaz (2020), Shah et al. (2020) and many other studies have examined the dimensions of service quality, the impact of service quality on passengers' behaviour, and differences in service quality perceptions across air markets. SERVQUAL has been extensively used in many service industries and aviation; however, researchers realised that AIRQUAL was a more specialised tool needed to measure service quality in the airline industry. AIRQUAL, which has five dimensions: airline tangibles, terminal tangibles, personnel, empathy, and image, was proposed to evaluate airline service quality from passengers' perspectives (Bari et al., 2001). The applicability of this industry-specific tool has been verified by empirical testing and validation in a variety of cultural situations like, North Cyprus National Airline (Ekiz et al., 2006), Pakistan International Airlines (Ali et al., 2015) and Egyptair (Abdel Rady, 2018). Recent studies have further highlighted the significance of AIRQUAL (Alotaibi, 2015) since it continues to anticipate passenger satisfaction and loyalty in the highly competitive airline market (Farooq et al., 2018).

Although there is an expanding body of literature on measuring service quality, more survey-oriented and generally similar research methodologies are employed. However, there are limitations to traditional survey-based tools like SERVQUAL and AIRQUAL. The main limitation is that these measurement instruments restrict customer experiences to pre-defined items like their dimensions. Service quality is evaluated within the scope of these dimensions and cannot be exceeded due to the nature of surveys (Duan et al., 2016). Secondly, these measurement instruments require significant investment in time and resources. The preparation, data collection, analysis, and decision-making based on the findings can be time-consuming and resource-intensive (Chakrabarti et al., 2018). Moreover, service expectations or issues may evolve during this process, which could mean that all the time and resources spent might be wasted. Consequently, given the constraints of SERVQUAL and AIRQUAL, research is needed to investigate this concept from the consumer perspective by analysing online customer reviews.

Recently, customer reviews have started to be considered in service quality studies as unstructured and valuable data sources (Lucini et al., 2020). Customer reviews provide valid information for examining past customer experiences, and compared to traditional surveys, they can offer comprehensive and real-time understanding (Chakrabarti et al., 2018). Therefore, this study investigates airline service quality dimensions by exploring the connection between passengers' emotional responses and their experiences with airline services, as reflected in their online reviews. The study also aims to reveal the relationship between the identified and SERVQUAL dimensions. Through this approach, the study tries to confirm the reliability of SERVQUAL in the current airline industry and concurrently uncover new perspectives on the concept of airline service quality. The reason for focusing on the dimensions of SERVQUAL rather than AIRQUAL in this study is the broad applicability of SERVQUAL as an established framework that allows for cross-sector comparison.

The study has made several contributions to theory and practice. Theoretically, it enriches the existing literature fields of airline service quality and the application of machine learning and text mining in social sciences. By evaluating service quality from pre-defined dimensions and consumer perspectives, the study adopts a more holistic approach to comprehensively understand passengers' expectations, perceptions, feelings, and experiences regarding airline service quality. In addition, the study challenges the traditional generic service quality scale (SERVQUAL) and advocates the inclusion of new service quality dimensions for measuring service quality; thus, it offers new avenues for future research. Moreover, despite studies employing text mining techniques/methods like topic modelling and sentiment analysis (Rasool and Pathania, 2021; Jeon et al., 2022), airline literature remains a significant gap. Also, compared to previous text mining studies in this field of research, the size of data analysed in this study is unprecedented, specifically with the inclusion of 100 diverse airlines. This increases the study's uniqueness by providing a deeper insight into the formation of service quality dimensions across different contexts and broadening the generalizability of the findings.

Since the study provides a deeper insight into passengers' emotional responses and experiences towards airline services worldwide, airlines can understand their customers' expectations, needs, and wants, identify specific areas for improvement, and tailor their services more effectively. This is critical for their customer experience management because improved service processes and overall quality result in increased customer satisfaction, which fosters loyalty and drives higher profits (Hussain et al., 2015; Jiang and Zhang, 2016). Furthermore, this study provides opportunities for airlines to benchmark themselves with others, allowing them to identify competitive strengths and areas for strategic development. Lastly, the study encourages academics and practitioners to use big data, machine learning and text-mining techniques to keep up with evolving consumer preferences. The practical outputs of the study can be extended to other service sectors like hospitality, healthcare, etc., even though the study is conducted on the airline industry because these sectors are interconnected and usually have similar concepts.

The study is structured as follows. The second section provides information about the text mining methods used in this study, explaining their application and the steps of the analysis process. The third section presents the study's results through detailed descriptions and visualisations. The fourth and last sections discuss the implications for academia and practitioners, the limitations of the study, and the directions for future research.

Methodology

Data collection and preprocessing

For this study, a comprehensive dataset was extracted from the Skytrax platform. The selection of the Skytrax platform is justified for the following reasons:

•Skytrax is respected and recognised by most airlines and airports in the industry as a benchmark for quality standards,

•It creates a venue not only for evaluating pre-defined elements but also provides a space for passengers to share their distinct experiences,

•It consists of a comprehensive amount of data and types of data,

•It is accessible to both reviewers and readers,

•It is credible since travellers/reviewers can share their experiences and opinions (Kilic and Cadirci, 2022).

The data gathered from the website covers a diverse mix of quantitative and qualitative data, including numerical rankings, binary choices, and textual feedback. A typical Skytrax comment begins with the title, reviewer's name, country, date of the comment, and verification status of the flight ticket, followed by the textual content of the comment. There is also an overall rating, where passengers assign a value from 1 (least favourable) to 10 (most favourable). Then, the reviewer answers parts like the type of traveller, seat type, route, and date flown. Following this, the section for star ratings appears, where the reviewer evaluates categories such as seat comfort, cabin staff service, food and beverages, inflight entertainment, ground service, Wi-Fi and connectivity, and value for money by giving ratings (stars) from 1 (least favourable) to 5 (most favourable). The comment concludes with a binary response to "Would you recommend the airline?" indicating either yes or no.

For this study, data from Skytrax's top 100 airlines of 2023 were collected in December 2023. Customer reviews of these airlines, posted between January 2013 and December 2023, were analysed. The sample is limited to 10 years due to the unavailability of data for all 100 airlines before this timeframe. The dataset for this study comprises 78,577 customer reviews, which presents a substantial corpus for analysing service quality perceptions in the airline industry.

Raw text datasets contain irrelevant information, punctuation, and emojis that may affect results. To improve the quality and effectiveness of the analysis, cleaning the data and ensuring that only relevant information is retained is critical. Therefore, preprocessing, which ensures data consistency, is one of the most critical initial steps in text mining analysis (Denny and Spirling, 2018).

Before starting the analysis, preprocessing was completed to clean the dataset and make it suitable for analysis. Preprocessing steps include tokenisation, where sentences and phrases are broken down into individual words, and stop word removal, where words are common in English and specific to this study (Li et al., 2022). In addition, punctuation, numbers, icons, and whitespaces were eliminated, and all words were converted to lowercase to ensure consistency. Finally, the fully processed dataset was prepared for analysis.

Topic modeling

Topic modelling has become a popular analytical method for assessing data, and it is widely used as a statistical technique to uncover latent variables within extensive datasets (Vayansky and Kumar, 2020). This unsupervised machine learning strategy presumes a specific probabilistic relationship exists between observed and unobserved variables within a dataset (Steyvers and Griffiths, 2007). As a probabilistic generative model, it has attracted attention from various research domains, including marketing analytics and has been used for text mining and information retrieval (Liu et al., 2016). It is beneficial with large volumes of unstructured text data, such as customer reviews, social media posts, or academic papers.

While several versions exist, the most employed topic modelling method is "Latent Dirichlet Allocation" (LDA), which was developed by Blei et al. (2003). LDA uncovers and describes hidden thematic patterns in sets of text documents. According to the operational methodology of this research model, every document contains topics that can be identified in every document by extracting word probability distributions (Vayansky and Kumar, 2020). It mainly identifies patterns and clusters within the textual data, groups words and phrases that can be interconnected, and then classifies them under topics (Moro et al., 2019).

The output of LDA typically consists of:

- A list of topics and words most associated with each topic.
- For each document, a distribution of each topic.

This analysis method provides detailed information extracted from large text documents without manually reviewing every document. In addition, it is beneficial for discovering latent themes, organising large text documents, and summarising the content of text data (Boyd-Graber and Mimno, 2017).

This method was employed in this study. This study employed this method to analyse customer reviews to identify key themes in passenger feedback and understand the main areas of concern or satisfaction in airline services.

The last significant step for this analysis is calculating coherence scores, an essential tool for measuring interpretable and meaningful topics (Röder et al., 2015). Mainly, the number of topics suitable for research models have higher coherence scores. (Agrawal and Menzies, 2018). Coherence scores were preferred in this research to find the ideal number of topics. The ideal number of topics and related terms were listed. The authors named each topic after reviewing the literature.

Sentiment analysis

Sentiment analysis, which is one of the ways of applying natural language processing (NLP) (Wankhade et al., 2022), is a frequently used method to reveal emotional intent or subtle emotions (Taboada, 2016). It is a valuable tool for extracting emotions about service quality from user-generated content (UGC), like customer reviews (Martin-Domingo et al., 2019). It includes determining the text's contextual polarity by exploring if it has a positive, negative, or neutral attitude (Devika et al., 2016).

There are two different ways of conducting sentiment analysis. One lexicon-based approach involves using a dictionary containing polarity information for emotion-related words (Taboada et al., 2011). Each term in the lexicon has a sentiment score, and the overall sentiment of the text is calculated by aggregating these scores.

The other approach, text classification, entails creating classifiers from labelled text samples. A Significant amount of labelled training data and computational resources are required for this analysis. (Mullen and Collier, 2004).

This study selected a lexicon-based approach to characterise customers' sentiments and calculate sentiment scores. Natural Language Toolkit (NLTK) library and Vader in Python were used to reach this goal. The Natural Language Toolkit (NLTK) is one of the Python libraries with a vast range of tools and resources needed to complete language processing tasks (Hardeniya et al., 2016). VADER, frequently preferred for sentiment analysis of social media texts, was used in this study to examine polarity (positive/negative/neutral) and sentiment intensity (Borg and Boldt, 2020). This revealed passengers' positive or negative sentiments towards different service topics under the primary dimension of airline services.

Results

In this study, before identifying the topics, the coherence score, which represents similarity and consistency between words within the topics (O'Callaghan et al., 2015), was calculated using the Gensim library in Python. The optimal number of topics was attained as 14 topics in Figure 1.

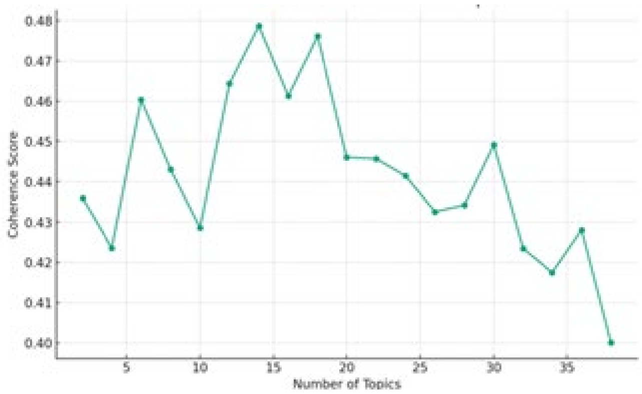

Figure 1: Coherence Score vs. Number of Topics

Source: Authors.

Next, topic labels were assigned to each topic, and the most frequent terms were categorised under a specific topic based on their probabilities, as shown in Table 1. The authors named These word groups under the main subject headings most frequently found in the literature. For example, words like delay, flight time, waiting time, airport, and minute are collected under the subject heading "flight delay" in the literature and therefore named in this way.

Table 1: Topic-Term Assignments

Topic name	**Terms**
Flight Delays	delay, flight hours, waiting time, airport, minutes
Airline Customer Service	call centre, communication, customer service, return, contact
Airport Accessibility	bus, shuttle, city centre, airport access, ticket
Airline Ticketing	booked ticket, night, days, early flight, problem
Aircraft Interior Comfort and Cleanness	seat, economy comfort, lightning, legroom, fee
Refunds and Cancellations	refund, end, last minute, missed, weather
In-flight Services and Crew	staff, cabin crew, entertainment, option, friendly
Baggage Handling	luggage, baggage handling, bag, conveyor, far
Check-in	check-in, employee, extra, long queue, service
In-flight Meals and Beverages	meal, water, served, drink, hot beverages
Passenger Experience	plane, arrival, gate, convenience, airport
Cabin Classes	business, class, lounge, premium, bar
Seat Arrangement	seat arrangement, family, group tickets, together, passenger number
Airline Network (Routes)	network, destination, point, hub, routes

Source: Authors.

The identified topics which are flight delays (Pakdil and Aydın, 2007), airline customer service (Chow, 2014), airport accessibility (Bogicevic et al., 2013), airline ticketing (Ganiyu, 2016), aircraft interior comfort (Chou et al., 2011), refunds and cancellations (Jiang and Zhang, 2016), in-flight services and crew (Basfirinci and Mitra, 2015), baggage handling (Basfirinci and Mitra, 2015), check-in (Kagnicioglu and Ozdemir, 2016), in-flight meals and beverages (Pakdil and Aydın, 2007), passenger experience (Pakdil and Aydın, 2007), cabin classes (Yakut et al., 2015), seat arrangement (Miller et al., 2019), airline network (Mikulić and Prebežac, 2011), align with various service quality dimensions that have been extensively studied in previous research.

After the dimensions of the airline services were determined, whether these dimensions overlapped with the generic SERVQUAL dimensions was controlled. While doing this, the researchers manually checked previous studies and customer reviews in which the subjects were explicitly mentioned. The service dimensions of the study and their relationship with generic SERVQUAL dimensions are shown in Table 2. Although some topics match other studies, some have been renamed or newly included under different service quality dimensions.

Table 2: Service Dimensions and SERVQUAL Mapping

Dimensions of SERVQUAL	Service dimensions of the study	References
Tangibles	Aircraft Interior Comfort and Cleanness	Chou et al. (2011)
	In-flight Meals and Beverages	Pakdil and Aydın (2007)
	Seat Arrangement	In this study
Reliability	Airline Ticketing	Ganiyu (2016)
	Baggage Handling	Basfirinci and Mitra (2015)
Responsiveness	Airline Customer Service	Chow (2014)
	Flight Delays	Pakdil and Aydın (2007)
Assurance	Refunds and Cancellations	Basfirinci and Mitra (2015)
Empathy	In-flight Services and Crew	
New Dimensions	**Service dimensions of the study**	
Accessibility	Airport Accessibility	In this study
	Airline Network (Routes)	
Customisation	Cabin Classes	
Technology Integration	Check-in	
	Passenger Experience	

Source: Authors.

Sentiment analysis determined areas of satisfaction and dissatisfaction regarding passengers' emotional reactions to airline services categorised in this study. By calculating these emotions as scores, the areas for improvement in airline services were indicated. Instead of equal-weighted dimension calculations in traditional survey methods, different weights were obtained for each dimension in sentiment analysis. Therefore, measuring the degree of importance passengers give to different service dimensions helps airlines direct their resources more effectively and develop strategies to increase customer satisfaction. In this study, the sentiment analysis results on airline service quality dimensions show that passengers are generally satisfied with the airline experiences, as shown in Table 3.

Table 3: Sentiment Scores of Service Quality Dimensions

Dimensions	Sentiment Scores
Tangibles	0.269
Reliability	0.125
Responsiveness	0.124
Assurance	0.075
Empathy	0.091
Accessibility	0.175
Customisation	0.11
Technology Integration	0.169

Source: Authors.

According to the results, passengers are most pleased with the airline service's physical aspects and have the highest sentiment score (0.269). This is followed by Accessibility (0.175) and Technology Integration (0.169), while Assurance (0.075) and Empathy (0.091) have the lowest scores and indicate potential areas for improvement. This analysis offers valuable guidance for the airline to retain its strengths and focus on improving areas with relatively lower scores to improve overall customer satisfaction further.

Discussion

As a service industry, the airline industry depends on tangible cues to shape passengers' perceptions of service quality and to enhance the overall travel experience. In this study, it was found that the following three physical aspects are the most significant for airline passengers among the various tangible offerings "Aircraft Interior Comfort and Cleanness", "In-flight Meals and Beverages", and "Seat Arrangement" were grouped under "Tangibles" dimension. Firstly, aircraft interior comfort is the physical element contributing to passenger comfort, such as the cabin's cleanliness and maintenance and the aeroplane's size. Despite the similarity with the previous one, seat arrangement is another vital tangibility element beyond merely providing spacious and ergonomically designed seats. This element involves the configuration of seating to accommodate various passenger needs. This element was not included separately in other SERVQUAL studies, but in this study, seat arrangement was categorised as a distinct element under the "Tangibles" dimension. Moreover, in-flight meals and beverages are offered to passengers during their journey, and the presentation, quality, and variety of meals and beverages can influence passengers' perceptions of the airline's service quality (Han et al., 2019).

"Airline Ticketing" and "Baggage Handling" are closely tied to the "Reliability" dimension. Passengers expect airlines to process their flight reservations quickly and accurately, to be immediately informed of any potential delays or cancellations, and to avoid encountering such problems. Baggage handling is another element related to the reliability dimension. Passengers want to trust airlines with their belongings, expecting careful handling and timely delivery of their luggage to the correct destination. Shortcomings in these two elements can lead to airlines failing to meet passengers' reliability expectations, resulting in dissatisfaction and a negative perception of their overall service quality (Basfirinci and Mitra, 2015).

"Airline Customer Service" and "Flight Delays" are found closely related to the "responsiveness" dimension. When passengers face problems like flight delays during their service experiences, they expect assistance from the airline (Pakdil and Aydın, 2007; Huang, 2010). Airlines with responsive customer service consisting of necessary channels and well-trained service staff can handle crisis situations effectively, increase customer satisfaction, build trust, and establish a reputation for responsiveness in the highly competitive airline industry.

In this study, "Refunds and Cancellations" is found to be closely related to the "Assurance" dimension. When passengers need to cancel or change their airline services, they anticipate a convenient and trustworthy process. If airlines have clear steps to follow, necessary policies, efficient procedures and knowledgeable service employees for refunds and cancellations to their passengers, they can provide a seamless experience, even under challenging conditions (Basfirinci and Mitra, 2015).

"In-flight Services and the Crew" are related to the "Empathy" dimension. Passengers love to have individualised attention during the service processes, and when they get this attention from the service employee, their likelihood of being satisfied with the service increases (Chou et al., 2011).

Moreover, this study proposed three new dimensions, which are "Accessibility", "Customization", and "Technology Integration". Firstly, the accessibility category includes airport accessibility and airline networks. Airport accessibility is getting to the airport conveniently for passengers and affects their perceptions of the airline's quality (Barus et al., 2024). Therefore, it should be considered while evaluating overall service quality. While airport accessibility has frequently been cited as an essential dimension of airport service quality, it is also recognised as a component of overall airline service excellence. Another term tied to this dimension is airline network, which includes all destinations they serve and is an air service attribute perceived as necessary by passengers (Zhang, 2012). While previous studies like Pakdil and Aydın (2007) and Chou et al. (2011) categorised airline networks under different dimensions, this study places it under the Accessibility dimension. This is because an airline's network, including destinations, hubs and routes, directly affects the ability of passengers to access various destinations. In other words, the network defines the scope and reach of an airline's service offering, affecting market coverage and connectivity, which in turn is related to the accessibility of the network to the destinations, i.e. its physical accessibility. Therefore, in this study, the airline network (routes) is categorised under accessibility after reviewing the passengers' comments to represent better its role in determining the service quality from the perspective of passenger access and convenience.

"Customisation" is a new dimension incorporated within the SERVQUAL scale. By integrating cabin class customisation into service quality measurement, airlines gain information for differentiating offerings, optimising revenue, and remaining competitive in meeting evolving passenger needs (Martins et al., 2024). Customisation can enhance customer loyalty and satisfaction (Coelho and Henseler, 2012); thus, it should be examined with a more specific focus as a dimension of service quality.

"Technology integration" is a new dimension proposed for the scale covering both "Passenger Experience" and "Check-in" processes. Since technology is a critical element affecting customer preferences and loyalty in today's competitive environment (Zhou, 2024), integrating technology affects passenger experience at multiple touchpoints throughout their journey in terms of time and convenience. In today's digital age, customers prefer technological solutions in airline service processes starting from ticket reservation and check-in (Balasubramanian and Francis, 2011), and even technologies are critical elements affecting customer preferences and loyalty (Zhou, 2024). These technological options, such as online check-in, mobile boarding passes and self-service kiosks at airports, have changed the check-in process by reducing waiting times and improving passenger experience by offering more convenience. Due to these interdependencies, passenger experience and check-in are grouped under the technology integration dimension. Additionally, as airlines continue to innovate, new technologies such as biometric scanning will continue to transform the check-in process and the entire passenger experience (Negri et al., 2019), making it impossible to separate passenger experience from technological innovation, making this dimension even more meaningful. As a result, technology integration is an essential factor to consider when evaluating service quality.

The sentiment analysis conducted in this study, which quantitatively measures the emotional tone in passengers' reviews, is correlated with happiness and satisfaction levels. While positive sentiment scores generally indicate higher levels of happiness and satisfaction, negative scores represent dissatisfaction or unhappiness with the service offerings. While the general feeling was found to be close to positive, it was found that passengers were most favourable with the Tangibles, Accessibility and Technology Integration. However, they were not very satisfied with the Assurance and Empathy. This shows that airlines need to improve in these areas.

The study contributes to academic studies both theoretically and methodologically. Firstly, the study paves the way for reevaluation and refinement of existing frameworks by expanding the understanding of service quality beyond the traditional dimensions. Mainly, it challenges the most generic measurement of service quality, SERVQUAL. As consumer perceptions of service quality have evolved significantly, with increased and diversified expectations from services, these changes make predetermined patterns and variables unsuitable for measuring service quality (Ladhari, 2009). For the studies to be more accurate and reflect the real world, it is crucial to identify or prefer the most up-to-date service quality dimensions. The new dimensions proposed, accessibility, customisation, and technology integration in the study, create a new focal point for future studies.

Another undeniable contribution of the study is methodological. In this study, text-mining techniques, including topic modelling and sentiment analysis, were applied to online customer reviews to gain insights into passengers' expectations and evaluate their overall service experiences. These types of computational methods are more advanced to uncover underlying themes, sentiments, and patterns that can inform a deeper understanding of customer perceptions and experiences (Geetha et al., 2017), especially considering the limitations of survey-based measurements of service quality due to their subjective nature, potential for response bias, inability to capture all aspects of the customer experience, small sample sizes, cost and time constraints, difficulty in interpretation, and inability to capture real-time feedback (Wan and Gao, 2015; Büschken and Allenby, 2016).

The remaining relevance of service quality as a research subject is emphasised by its multidisciplinary appeal and wide-ranging applications across various industries. The ever-evolving nature of service needs and consumer expectations necessitates continued exploration, particularly in developing a deeper understanding of consumer perspectives. This study aims to redirect research in this domain by introducing novel service quality dimensions, thereby carving out a new area of research. It advocates for adopting alternative methodological approaches like text mining, specifically highlighting the potential of machine learning algorithms to measure service quality. By drawing attention to the increasing importance of machine learning techniques in marketing research, this study lends credence to the belief that these algorithms will play a pivotal role in advancing the field of service quality, making significant contributions to its future development.

This study offers actionable suggestions that can benefit practitioners in the airline industry to improve service quality. By employing text mining techniques on a massive corpus of online reviews, the analysis reveals novel dimensions of airline service quality that transcend traditional SERVQUAL measures. These newly discovered dimensions provide a contemporary, consumer-centric lens through which airlines can strategically prioritise enhancement opportunities. A detailed examination of passengers' reviews and emotions indicates the touchpoints and service areas with the most significant influence over customer experience, customer satisfaction and loyalty. Since understanding consumer dynamics is necessary for providing services that meet their expectations and survive in competitive markets like the airline industry (Mikulić and Prebežac, 2011), service quality dimensions mentioned in this study can help airlines tailor their services. Potential enhancements can be made by offering staff training programs, providing effective customer services, optimising operational protocols, and developing service delivery technologies.

Furthermore, the study leverages big data and computational techniques to analyse text data. The study encourages airlines to adopt a data-driven, consumer-focused mindset by underlining the power of analytics for continuous improvement and competitive advantage. This methodological advancement enhances the understanding of airline service quality and provides a framework that can be applied to other industries facing similar challenges in analysing large volumes of textual data.

There are still limitations of the study. One limitation of the study is that it only focused on the data source, Skytrax, which may restrict the generalizability of the findings. Additionally, regarding the generalizability of the findings, excluding passengers who do not post online reviews in the study is one of its limitations. For further research, it is recommended that different review websites like Tripadvisor, Yelp and Google Reviews be included in the study. An alternative data source for collecting consumer opinions about airline services, such as social media platforms where people share their opinions without any constraints, could be considered (Yee Liau and Pei Tan, 2014). Another limitation is that the study took all airline accounts as a single group and did not cluster them based on their origins, the geographical regions served, or business models. Similarly, passengers were not analysed in different segments. Future studies can consider these distinctions because more detailed consideration reveals how varying factors affect passengers' emotions and experiences with airline services. Having insights for every group can lead to more targeted and effective strategies for improving service quality and customer satisfaction. Moreover, sentiment analysis may occasionally face challenges in interpreting sarcasm and complex emotions. Future research could complement sentiment analysis with more sophisticated tools like Bidirectional Encoder Representations from Transformers (BERT). Lastly, future research can validate and further explore the new dimensions identified in this study across diverse contexts within the airline industry.

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