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Faculty of Business Economics

Master of Management

Master's thesis

A Sentiment Analysis of Customers' Complaints in the Airline Industry: The Case of Brussels Airlines

Rene-Eyves Chi Nche

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :

Prof. dr. Niels MARTIN

2022
2023

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Master of Management: Business Process Management

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ABSTRACT

In today's fiercely competitive airline industry, understanding customer sentiments and effectively resolving complaints have become essential for customer satisfaction and loyalty. In order to discover crucial insights that can help airlines improve their services and enhance customer experiences, this study focuses on sentiment analysis of customer complaints in the airline industry. It analyzes 2,259 TripAdvisor reviews of Brussels Airlines from January 2017 to November 2022. Only English reviews with ratings of "average," "poor," and "terrible" are considered. The research approach used is the Design Science Research Methodology (DSRM), employing a methodological artifact that combines the analysis of customer complaints and their sentiments. While sentiment analysis is carried out using Azure Machine Learning to determine the sentiments (positive, negative, or neutral) of the airline customers, MAXQDA software is used in identifying the most prominent airline customer complaints. The analysis of customer complaints shows that among other airline customers' complaints, luggage issues, flight delays, flight cancellations, and food quality are the most frequently expressed complaints. The sentiment analysis findings reveal overall customer dissatisfaction with the airline's services. By combining the analysis of customer complaints and sentiment analysis into a single research paper, this study adds to the body of knowledge by giving airlines an in-depth understanding of how to use customer feedback to quickly understand their customers' sentiments and promptly address their complaints. The knowledge gathered will assist airlines in transforming customer complaints into opportunities for service enhancement, fostering customer satisfaction, and gaining a competitive edge in the industry.

Keywords*: Airline industry, customer complaints, sentiment analysis, Design Science Research Methodology (DSRM), MAXQDA, Azure Machine Learning.*

ACKNOWLEDGMENTS

I want to thank the Almighty God for giving me the strength, courage, and inspiration to work on and finish my thesis successfully.

Additionally, I would like to extend my sincere gratitude to my supervisor Prof. dr. Niels Martin, for his never-ending encouragement, direction, and patience. I am incredibly appreciative of his kindness, perseverance, tremendous assistance, creative suggestions, and insightful remarks, all of which helped my thesis come together. I was extremely motivated to work hard on my thesis by his supervision style.

Last but not least, I want to express my gratitude to my family, close friends, and anybody who has helped me directly and indirectly. I genuinely appreciate everyone who prayed for me and offered encouraging ideas. Without your steadfast help, this adventure could not have been accomplished.

1 INTRODUCTION

The aviation industry is one of the world's well-known and well-established industries. Airline flights began in 1919 following the First World War, but the industry did not completely take off until the Second World War. Travel and tourism have had a remarkable impact on the airline sector, growing at an incredible rate and contributing 10% of the global gross domestic product (GDP), thus making this market very competitive (Akyuwen, 2015).

According to O'Kelly (2016), the airline industry is globally active, but it faces challenges such as severe competition from new airlines seeking space in the airline industry and inadequate resolution of customer complaints. To obtain a competitive advantage, airlines must understand that customers highly value service-related aspects, such as high-quality customer service and on-time arrival, so airlines must ensure that these values or preferences are satisfied (Wang et al., 2018). Even though airlines strive to provide services with zero-defect, there is still a possibility of service failures in the industry (Schoefer, 2005). Rejikuma (2015) defined service failure in an airline as any occasion where the airline does not meet or surpass the expectations of its customers in providing a safe, effective, and enjoyable travel experience. Some common service failures in this sector that prompt airline customers to complain include inadequate facilities or amenities, lost or damaged baggage, poor customer service, and overbooking (Rejikumar, 2015; Harrison-Walker, 2012).

Even though service failures frequently result in customer complaints, these complaints play a crucial role in the airline industry. Airline customer complaints often offer insightful feedback about the airline's services and facilities and essential areas where airlines can enhance the quality of their customer service (Chi et al., 2008). Therefore, airlines can improve customer satisfaction, service quality, operational practices, and customer loyalty by being aware of these issues and swiftly resolving them (Chi et al., 2008). Again, Mattila & Mount (2003); Sparks et al., (2013) revealed that being aware and responding to customer complaints promptly and effectively can increase customer retention, resulting in favorable online reviews, which can help an airline stand out. Also, Kim et al., (2011); Munar & Jacobsen (2014) revealed that resolving complaints quickly and effectively displays the airline's dedication to providing excellent customer service and can aid in reestablishing trust, fostering a positive brand image, and fostering positive word-of-mouth airlines which may contribute in helping the airlines to stand out in a highly competitive industry.

Nevertheless, even though airlines aim to regain customer trust by responding to customer complaints and increasing customer satisfaction, Rejikumar (2015) and Harrison-Walker (2012) revealed that airlines' responses to customer complaints sometimes worsen the situation. An example is the case where frontline staff suggests to customers that complaining about aircraft seat comfort can not be handled. Such concerns have led to customers withholding their complaints. Also, some airline regulations are complicated and challenging for customers to comprehend, making it confusing when attempting to file a complaint. These complex regulations discourage some airline customers from complaining because they cannot understand the complaint procedures and unclear guidelines (Abhyankar & Nyilasy, 2012).

Before the availability of the Internet, airline customers needing to file a complaint had to voice their complaints in person to the airline or had to complete complicated forms or questionnaires that most of them could not understand (Korfiatis et al., 2019). As such, these traditional ways of gathering customer feedback through distributing, collecting, and analyzing questionnaires took time and were frequently inaccurate (Wan & Gao, 2015). Lucini et al. (2020) also discovered that airline customers carelessly or randomly filled out many survey forms, and this information distorted the airline's view of customer satisfaction.

Nowadays, the advent of the Internet and the accessibility of social media platforms like Facebook, Twitter, Skytrax, and TripAdvisor has made it easier for airline customers to express their complaints or satisfaction via reviews (Winch, 2011). Since these third-party travel websites, like TripAdvisor or Skytrax, are not connected to any commercial interests, they have higher credibility, making them more liked and used by travelers (Tsao et al., 2015). As a result, many more airline customers write online reviews describing their satisfaction or dissatisfaction with an airline's services after they have used it to travel (Gretzel & Yoo, 2008). Given that airline customers write these reviews, they are perceived as relatable and reliable compared to intrusive advertising strategies (Lee & Heejung, 2016). These airline customer reviews are essential as they aid airlines in identifying development areas, addressing customer complaints promptly, forecasting service demand, and enhancing overall customer satisfaction and service quality (Ganu et al., 2009; Filieri & McLeay, 2014).

Prior researchers have utilized online reviews from customers to examine customer complaints in various service industries, including hotels (Kim et al., 2009; Smith et al., 2002) and restaurants (Mattila & Patterson, 2004; Siu et al., 2013). These studies showed that customers' online reviews were great data sources for assessing the aspects of complaints. Similarly, in the airline industry, researchers such as Souza (2015), Atalik (2007), and Güre et al. (2013) have used internet reviews to investigate customer complaints in the airline business. These researchers' studies focused on inventorying the most common complaints experienced by domestic and international airline customers and comparing or classifying them according to their typology. Nevertheless, these researchers' studies frequently lacked a thorough knowledge of how customers felt about utilizing the airlines' services, meaning that no sentiment analysis was conducted.

Sentiment analysis is the computational analysis of online reviews of people's feelings, attitudes, and perspectives about a product, event, or organization to determine whether they are neutral, negative, or positive (Kasture & Bhilare, 2016; Li & Wu, 2010; Thomas et al., 2011). Similarly, only a few academics, such as Das et al. (2017) and Rane & Kumar (2018), attempted sentiment analysis in the airline industry but did not study the factors that led to airline customers' negative, positive, or neutral sentiments. Thus, a research gap exists in comprehensively understanding customer complaints and sentiments in the airline industry. Although previous research on customer complaints and sentiment analysis in the airline industry was relevant, it was insufficient. To successfully address customer issues and improve the entire customer experience, airlines require a thorough grasp of customer complaints and sentiments in a single research paper. By filling this knowledge gap, airlines would be able to respond more promptly and efficiently to customer problems, leading to improved customer satisfaction.

Therefore, this study seeks to bridge the gap in previous research by offering airlines a consolidated view of customer complaints and sentiment analysis in a single research paper. The study aims to advance prior research by adopting a Design Science Research Methodology (DSRM) approach proposed by Peffers et al. (2008). DSRM is an iterative problem-solving strategy employed in information systems research to create, evaluate, and refine artifacts (e.g., models, methods, frameworks) that address specific challenges. By integrating theory and practice, this methodology generates new knowledge and design concepts applicable in real-world contexts (Hevner et al., 2004).

The Design Science Research Methodology (DSRM) is used in this study to conduct a combined analysis of customer complaints and sentiment in the context of Brussels Airlines, serving as the airline industry's case study. The study adheres to the DSRM's six steps: problem identification and motivation, defining the objectives of a solution, design and development, demonstration, evaluation, and communication (Peffers et al., 2008). Firstly, the online reviews of Brussels Airlines on TripAdvisor will be analyzed to identify the most prominent complaints from customers. Secondly, sentiment analysis will be conducted using a lexicon-based classification method to assess customer sentiment toward the airline's services. By utilizing DSRM, the study seeks to offer a thorough understanding of customer feedback and sentiments, enabling the generation of insights and artifacts to improve service quality and client satisfaction for Brussels Airlines.

To address the need for resolving customer complaints and improving satisfaction in the airline industry, the study formulates the following research questions: ***1) What are the most prominent complaint categories expressed by airline customers? 2) How can sentiment analysis be used to determine customer sentiments towards airline services?*** To answer the first question, MAXQDA, a qualitative data analysis program, will be utilized to identify and classify the most common complaints made by airline customers in their online reviews. For the second question, Microsoft Azure Machine Learning, a lexicon-based sentiment analysis tool, will be employed to analyze these reviews and determine customer sentiments.

Through the results of this study, a revelation of the frequency and types of customer complaints and the sentiments of Brussels Airlines customers would be obtained. These results will permit Brussels Airlines to self-evaluate its performance and gain insights into specific service areas that require improvement, allocate resources effectively, and align its strategies with customer expectations. The availability of this information, in accordance with Kim & Cha (2002) and Chi & Qu (2008), would help service managers of airlines such as Brussels Airlines in making strategic decisions, respond to customer issues, prevent similar complaints in the future, raising the standard of its overall service, improve customer satisfaction and foster stronger relationships with its customers. Also, the results of this study will assist Brussels Airlines to be able to segment its customers based on their preferences, likes, and dislikes. This segmentation can help the airlines create a personalized market campaign to target a specific customer segment to enhance their experience or satisfaction.

Lastly, the findings of this study will be significant to scientific literature as it proposes a methodological advancement based on the design science research methodology (DSRM), which consists of steps that can assist airlines in analyzing their customer reviews to comprehend their sentiments and complaints. This development will improve current theories and models in the airline sector related to sentiment analysis and customer complaints, giving researchers new perspectives (Duan et al., 2008).

Although this study contributes to the airline industry's knowledge, it has a few limitations. TripAdvisor was the primary data-gathering platform; hence, this study's results were restricted to that single website or social media platform. Also, only reviews written in English were considered for the study, excluding the opinions and potential complaints of other airline customers who posted reviews in other languages. Again, it is presumed that actual airline customers sincerely and truthfully wrote the TripAdvisor customer reviews of Brussels Airlines.

The remaining sections of this thesis are organized as follows: Section 2 presents the context and literature. In Section 3, the research methodology is covered. The analysis results are presented in Section 4. The results and constraints are discussed in Section 5. Section 6 of the thesis outlines several recommendations for more research.

2 LITERATURE REVIEW

As indicated in the study's earlier section, customers of airlines frequently encounter service failures, including price increases for tickets and flight cancellations, which make them uncomfortable with the airline's services. However, because it's critical for airlines to be aware of the factors that lead to customer complaints and to understand how their customers feel about their services, this section of the study thoroughly evaluates previous studies on customer complaints and sentiment analysis.

With the study's goal in mind, this section of the study begins by addressing what customer complaints are all about in Section 2. and then provides an overview of complaints in the airline industry in Section 2.2. Further, a summary of sentiment analysis is covered in Section 2.3, including information on the various sentiment approaches and levels of Classification. Finally, Section 2.4 addresses the associated works of sentiment analysis in the airline industry.

2.1 Customer Complaints in the Airline Industry

Due to the rapid growth and the entry of new airlines into the airline industry, the airline sector is characterized by intense competition. (Cambra-Fierro & Melero-Polo, 2017). Hence efforts to lower customer complaints and improve customer loyalty and satisfaction are warranted to acquire a competitive advantage in the market. A customer's complaint, as defined by Ateke et al., (2015), is an expression of dissatisfaction when a service failure occurs, and a customer makes this complaint to a service provider, third parties, or customer protection organizations. Customers can express their complaints in one of three ways: by ending their relationship with the service provider (exit), by speaking out in public (voice), or by remaining silent and continuing their previous relationship (loyalty) (Dowding et al., 2000).

According to Zhou et al., (2014), airline complaints, which are often an action taken by airline customers as a result of their discontent with airline services, are a significant indicator of bad airline service quality or service failure. Service failures, according to Maxham & Netemeyer (2002), are "any service-related mishaps or difficulties (actual or imagined) that occur during a customer's experience with an organization (airlines). Although there hasn't been much research on service failure in the airline business, Bramford and Xystouri (2005) revealed three complaints that airline customers frequently voice. These complaints include service interruptions such as frequent strikes, numerous flight delays (typically of a technical nature), and complaints about the attitudes of ground staff. Chen & Chang's (2010) also revealed that even the most excellent airlines occasionally suffer from service failures, such as overbooking or delayed flights. These failures may have a detrimental impact on the airlines' ability to generate revenue.

2.1.1 Ways of Filing Complaints to an Airline

Due to the advent of the Internet, airline customers who previously voiced their complaints in person to the airlines or via filing questionnaires have changed their behavior (Winch, 2011). Dissatisfied airline customers nowadays express their displeasure or complaint publicly, either directly on the airline's official page or through social media sites such as Facebook, Twitter, TripAdvisor, Youtube, and Skytrax (Dunn & Dahl, 2012). He et al. (2014) further confirmed that social media is helpful for customers to lodge grievances. Airlines have realized the value of these platforms not only for marketing purposes but also as communication channels. As a result, they provide features like chat rooms, blogs, email addresses, and rating/commenting systems to their customers to provide feedback (Novani & Kijima, 2012; Grancay, 2015).

2.1.2 Handling Airline Customer Complaints

After receiving a customer complaint about a service failure, airlines should start a complaint-handling process to resolve complaints from dissatisfied customers to maintain customer happiness and loyalty (Ateke & Kalu, 2016). When resolving a service failure in the airline industry, time is of the essence (Law, 2017). According to Mattila (2006), airline customers are more understanding and forgiving of errors if the airline can effectively handle and resolve the problems on time. A prompt reaction to customer complaints helps lessen bad word-of-mouth, according to Davidow (2003) and Karamata et al. (2017). According to Lee & Cranage (2017), responding quickly to customer complaints can help airlines reap a variety of benefits, such as enhanced repurchase behavior, increased customer loyalty, the advantages of good word-of-mouth marketing, and higher airline profitability.

To resolve these customers' complaints without much delay, La & Kandampully (2004) recommend implementing strategies such as providing customers with a range of options to fulfill their demands and engaging in open communication to explain the reasons for service failures. La & Kandampully (2004) further suggested that it is essential for airlines to have service recovery workers who are qualified specialists with the proper training and tools to handle the stress and frustration of disgruntled customers. As Mattila and Cranage (2005) also suggest, airlines should express genuine remorse for the poor quality of service and consider providing customers with concrete compensation, like coupons or discounted tickets.

2.1.3 Classification of Airline Customers' Complaints

The airline industry is particularly vulnerable to service failures, often resulting in customer complaints (Bejou & Palmer, 1998). Service failures can generally be divided into Outcome Failures and Process Failures (Chan & Wan, 2008). An outcome failure occurs when the customer does not receive the service they have paid for, whereas a process failure refers to an interruption in the provision of the indicated service (Johnston & Michel, 2008; Smith et al., 1999). Process failures, according to Smith & Bolton (2002), are primary causes by inaccuracies made by staff members who are providing the service, like an unwelcoming and unpleasant flight attendant. Outcome failures are equally related to the core service offering, meaning the service provider (airlines) failed to provide an essential element necessary to deliver the best service, such as comfortable seats on the flight (Souza, 2015). Outcome failures are more server than process failures as they are more likely to result in customer loss. As a result, when an outcome failure occurs, an airline works harder to restore services than when a process failure occurs (Chou et al., 2009). In the airline industry, overbooking, strikes, flight cancellations, and delays are some of the frequent causes of service failures. Due to the disruption of expected services and a failure to meet customer expectations, these situations frequently result in customer complaints (Bramford & Xystouri, 2005).

2.1.4 Benefits of Customer Complaints

When a service failure occurs, complaints from customers offer valuable insight that the service provider can use to identify and address operational issues, appease customers, win their loyalty, and avoid losing sales and revenues (Fornell & Wernerfelt, B, 1987; Kelley et al., 1993; Reichheld, 1993; Reichheld & Sasser, 1990). Haverila & Naumann (2010) also revealed that customer complaints stimulate business growth and success and can be used to improve a product or service.

2.2 Sentiment Analysis

Sentiment analysis is a multidisciplinary field that analyzes people's attitudes, emotions, and opinions about various entities, including products, services, people, organizations, events, and topics (Mäntylä et al., 2018). It is also referred to as sentiment classification, opinion mining, or polarity classification, among other terms. Since 2004, sentiment analysis has been examined from various angles and has steadily increased in popularity as a method for detecting peoples' emotions or opinions (Mäntylä et al., 2018). As of 2018, nearly 7,000 papers on sentiment analysis have been published, especially those concerning analyzing social media posts to predict the financial market rise or fall (Mäntylä et al., 2018).

2.2.1 Different Levels of Sentiment Analysis

Depending on how sentiment analysis (known as polarity classification) is used, sentiments may be positive, negative, or neutral (Yadollahi et al., 2017). Sentiment polarity identification can be made at three different levels of granularity: document, sentence, and aspect (Pang & Lee, 2008).

- **Document Level**: Regarding sentiment analysis at the document level, the entire document is written by one person and regarded as having only one opinion regarding a single object (be it a movie review, book review, or hotel review) (Liu B, 2015). The goal of sentiment analysis at the document level is to ascertain if a user likes (positive sentiment) or detests (negative sentiment) a specific object or entity (Jiang et al., 2011). Hence the document level looks at the **overall sentiment** of a text. For instance, if a user on a social media platform like Twitter tweets, *"I adore the new Zombieland movie #cinema.",* the job is to indicate whether the user likes or dislikes the film.
- **Sentence Level:** The goal of sentiment analysis at the sentence level is to categorize the sentiment represented in **each sentence** because a sentence is viewed as a distinct unit. Nevertheless, there is no great difference in the classification technique and algorithms used for sentiment analysis at the document and sentence levels (Liu, 2012). At the sentence level, sentiment analysis starts by **determining whether the sentence is objective or subjective**. The difference between objective and subjective sentences is that objective sentences contain facts, while subjective sentences contain opinions (Maas et al., 2011). Take the sentence *"Today's weather is sunny, and I love sunny days*." as an example. The first clause of the sentence, *"Today's weather is sunny*," is factual and objective in this instance. Since it does not convey any opinion about the weather, it is removed during the analysis (Maas et al., 2011). Therefore, only subjective sentences containing opinions are considered when conducting sentiment analysis at the sentence level.

- **Entity and Aspect-Level:** Unlike document and sentence levels, aspect-level sentiment classification in sentiment analysis is a more precise method (Pang & Lee, 2008; Li et al., 2010). **It seeks to identify the sentiment polarity (positive, negative, or neutral) for each element mentioned in a text or sentence.** For instance, consider the sentence, *"The restaurant has a* *reasonable price, but the food tastes awful.*" In this instance, the restaurant is the **entity**, and the cost and quality of the meal are the **aspects**. According to aspect sentiment classification, the pricing aspect would be given a positive polarity, while the food aspect would be given a negative polarity (Jing et al., 2015).

Tang et al., (2016); Wang et al., (2016) revealed that, due to the many applications of the aspect-based level of sentiment classification in fields like public opinion mining and e-commerce customer service, the aspect-based level of sentiment categorization has attracted increasing interest over the past ten years. However, aspect-based level sentiment analysis is a more complex or challenging task with several smaller tasks. These tasks include entity extraction, aspect extraction and classification, among others. The entity extraction tasks entail identifying and extracting entities such as persons, organizations, or locations from unstructured text and categorizing them according to pre-established categories. Aspect extraction and categorization entails detecting and extracting elements or aspects of a good, service, or entity from unstructured text and categorizing them into pre-defined categories (Liu, 2010) & (Liu, 2012).

2.2.2 Sentiment Analysis Approaches

There are many methods for analyzing textual data in sentiment analysis, and the chosen method depends on the type of data being examined. The approaches used in sentiment analysis can be divided into three categories (Anitha et al., 2013): (1) lexicon-based methods (Maynard & Adam Funk, 2011) (2) machine learning methods (Krouska et al., 2016; Troussas et al., 2013) and (3) hybrid methods that combine the first two (Li et al., 2020).

A) Lexicon-Based Approach

The Lexicon-Based approach to sentiment analysis is a methodology that uses sentiment lexicons or dictionaries to determine the sentiment polarity of text data. According to Ahire (2014), a sentiment lexicon, also known as a sentiment dictionary, is a collection of words (opinion words) associated with their sentiment orientation (positive or negative). Examples of positive sentiment adjectives are lovely, gorgeous, and astonishing. Negative feeling words, on the other hand, include horrible, poor, and nasty. By comparing words in a text with those in the dictionary, the lexicon-base sentiment classification tools such as SentiWordNet (Baccianella et al., 2010), SentiStrength (Thelwall et al., 2012), Azure Machine Learning, Vader, and Meaning Cloud utilize the sentiment lexicon databases for processing linguistic data and determining the polarity of the text.

Furthermore, coupled with the simplicity of the lexicon-based approach, Taboada et al., (2011) revealed that the lexicon-based approach is domain-independent, requires less time, is cost-free, and does not require a training and testing data set to classify sentiments. Also, this approach performs well in terms of accuracy in polarity prediction, sometimes even outperforming the machine learning approaches (Tan et al., 2008).

B) Machine Learning Approach

The machine learning approach of sentiment analysis is an approach that involves using computer algorithms to automatically classify data into different sentiment categories, such as positive, negative, or neutral (Mohri et al., 2012). The data used for classification can come from various sources like social media, customer reviews, or news articles. Before classifying the data, it is preprocessed to remove noise, such as stop words, special characters, and URLs. The preprocessed data is then split into two sets: a training set and a test set, and it's saved in the form of a spreadsheet, PDF, HTML, or JSON file. The training data set, which can either be a product or movie review, is used as input data for a machine learning classifier such as Naive Bayes (NB) or Support Vector Machines (SVM) to train the classifier to predict the sentiment of new, unexplored text data (Medhat et al., 2014). The classifiers' efficiency and accuracy in sentiment classification is subsequently evaluated using a test data set, such as a tweet or a Facebook post (Pang & Lee, 2004).

Even though using a machine learning approach to interpret data is beneficial, this sentiment analysis approach is challenging, computationally intensive, time-consuming, and slower than the lexicon-based method due to the extensive data training (Chekima & Rayner, 2018; Augustyniak et al., 2016). Additionally, a machine learning classifier's performance is more likely to degrade when applied to a different domain after being trained to be used on a particular dataset (Neviarouskaya et al., 2013).

C) The Hybrid Approach

The term "hybrid approach" in sentiment analysis refers to the combination of the machine learning approach and lexicon-based approaches (Medhat et al., 2014). According to Prabowo & Thelwall (2009), the main objective of this combination is to provide the highest and ideal outcomes of sentiment classification by using the relevant features and functionality of both lexicon and machine learning-based methods to overcome the shortcomings and constraints of both approaches. Researchers such as Malandrakis et al., (2013) and Sommar & M. Wielondek (2015) have combined several lexical and machine-learning-based techniques to develop unique and valuable hybrid tools such as Sail and pSenti.

2.3 Related Works of Sentiment Analysis in the Airline Industry

To conduct sentiment analysis, Adarsh & Ravikumar (2018) collected the tweets of airline customers from the Twitter accounts for Indigo Airlines, Emirates Airlines, and Qatar Airlines. After calculating the sentiment score and classifying the tweets of the airline customers based on positive, negative, and neutral sentiments, the researchers discovered that Emirates Airlines had more positive emotions from their passengers. Indigo Airlines had more negative sentiments, while Qatar Airlines had more neutral sentiment tweets.

Similarly to the research of Adarsh & Ravikumar (2018), Das et al., (2017) used 200 tweets of airline customers from the Twitter accounts of Emirates Airlines and Jet Airways to conduct sentiment analysis. These researchers utilized the Naive Bayes algorithm to classify the sentiments of these airline passengers into positive, negative, and neutral categories. To enhance the categorization of the sentiment classifier (Naive Bayes), they used Regression and Rapid Miner tools.

Also, to determine the sentiment of six major Indian Airlines, Hemakala & S. Santhoshkumar (2018) used tweets from these airline customers. The researchers began by cleaning the tweets using preprocessing methods. They then used deep learning to perform sentence-level analysis to represent the tweets as vectors. Afterward, they employed seven sentiment classification methods: Gaussian Naive Bayes, Decision Tree, Random Forest, SVM, K-Nearest Neighbors, Logistic Regression, and AdaBoost. The sentiment polarity accuracy provided by AdaBoost was the highest, with a value of 84.5%. The classifiers' accuracy levels were sufficiently high for the airline sector to use to improve customer satisfaction.

Lastly, Rane & Kumar (2018) utilized the tweets from the airline customers of six American airline companies to conduct sentiment analysis using Decision Trees, Gaussian Naive Bayes, SVM, K-Nearest Neighbors, Logistic Regression, and AdaBoost. The classifiers were trained on 80% of the data and tested on 20%. These researchers divided the sentiments expressed in the tweets into three groups (positive, negative, and neutral). With an accuracy of more than 80%, they noted that the logistic regression models, AdaBoost, random forest, and SVM performed well.

3 RESEARCH METHOD AND RESEARCH METHODOLOGY

This section of the study presents and describes several methodological concerns related to this study while also justifying why they were chosen. It is divided into two sections: The research method and the research methodology section, which has other subsections such as the design science research methodology(DSRM) approach, data collection, and data analysis.

3.1 Research Method

The study aimed to identify the most prominent complaints from airline customers (specifically Brussels Airlines) and determine how they feel about using their services. As a result, the research questions that shaped this study were: ***What are the most prominent categories of complaints expressed by airline customers? Also, how can sentiment analysis be used to determine how these airline customers feel about the airline services?*** Using data retrieved from TripAdvisor, which served as the primary data source for this study, a combined study comprising both an analysis of customer complaints and sentiment analysis was carried out to address these research questions.

In order to gather the necessary literature pertinent to the topic, a narrative literature review was conducted. A narrative review summarizes and evaluates the recent scholarly work on a specific subject. The two databases used for this study's research were Google Scholar and Web of Science, and the search for pertinent literature was refined to include only English-language journal articles or other publications published between 2000 and 2022 that were linked to customer complaints or sentiment analysis specifically in the airline industry. Keywords such as "online reviews about airlines," "airline complaints," "airline customer complaints," "customer satisfaction in airlines," "service failures," "service failure in airlines," "airline complaint handling," "sentiments analysis," "sentiment analysis approaches," "sentiment analysis granularities," "sentiment analysis in airlines," "qualitative analysis software" and others were searched in titles, abstracts and among key words to identify the articles that have investigated customer complaints and sentiment analysis in the airline industry from 2000. All possible synonyms of the keywords and keyword combinations used in previous academic studies related to the research question were used to ensure a coherent search (Snyder, 2019).

3.2 Research Methodology

Only a few researchers have attempted to conduct sentiment analysis and customer complaints in the airline industry. These researchers mostly used Skytrax and Twitter to gather the data for their studies. Additionally, these researchers only focused on sentiment analysis without finding the reasons influencing customer sentiment (customer complaints). Similarly, those focusing on customer complaints didn't look into the primary causes of the customers' positive, negative, or neutral sentiments toward the airlines; that is, they didn't conduct sentiment analysis.

As a result, this study is a combined exploratory study that aims to investigate the various prominent complaints made by airline customers and find out the sentiments (positive, negative, or neutral) of these customers after using airlines' services. In this regard, the Design Science Research Methodology (DSRM) proposed by Peffers et al., (2008), which spans from problem identification and motivation to communication, will be employed as the research approach to fulfill the study's purpose.

3.2.1 Design Science Research Methodology (DSRM)

Design science research methodology (DSRM) is a problem-solving approach that seeks to enhance human and organizational capabilities by creating unique and innovative artifacts such as methods, models, procedures, and instantiations (Hevner et al., 2004). These artifacts are specifically developed to address organizational issues and provide innovative solutions (Hevner et al., 2004; Gregor & Hevner, 2013). The DSRM is a prescriptive technique, as Gregor and Hevner (2013) demonstrated, where researchers design artifacts to overcome study goals and solve problems, and these artifacts can take various forms:

- Methods: Step-by-step procedures, such as algorithms and practices, outlining how to accomplish a specific task or objective.

- Models: Statements or propositions that outline a set of constructs to solve a problem, often represented through abstractions and visual representations.
- Constructs: Things used to define and address issues in a particular context. They include ideas, words, and symbols.
- Instantiation: Actual work based on constructs, models, or methods, implementing the designed artifacts in practical settings.

The design science research methodology (DSRM) is comprised of six activities: (1) Problem identification and motivation, (2) Define the objectives of a solution, (3) Design and development, (4) Demonstration, (5) Evaluation, (6) Communication (Peffers et al. 2008). Figure 1 below shows the graphical representation of the six steps adapted to this study.

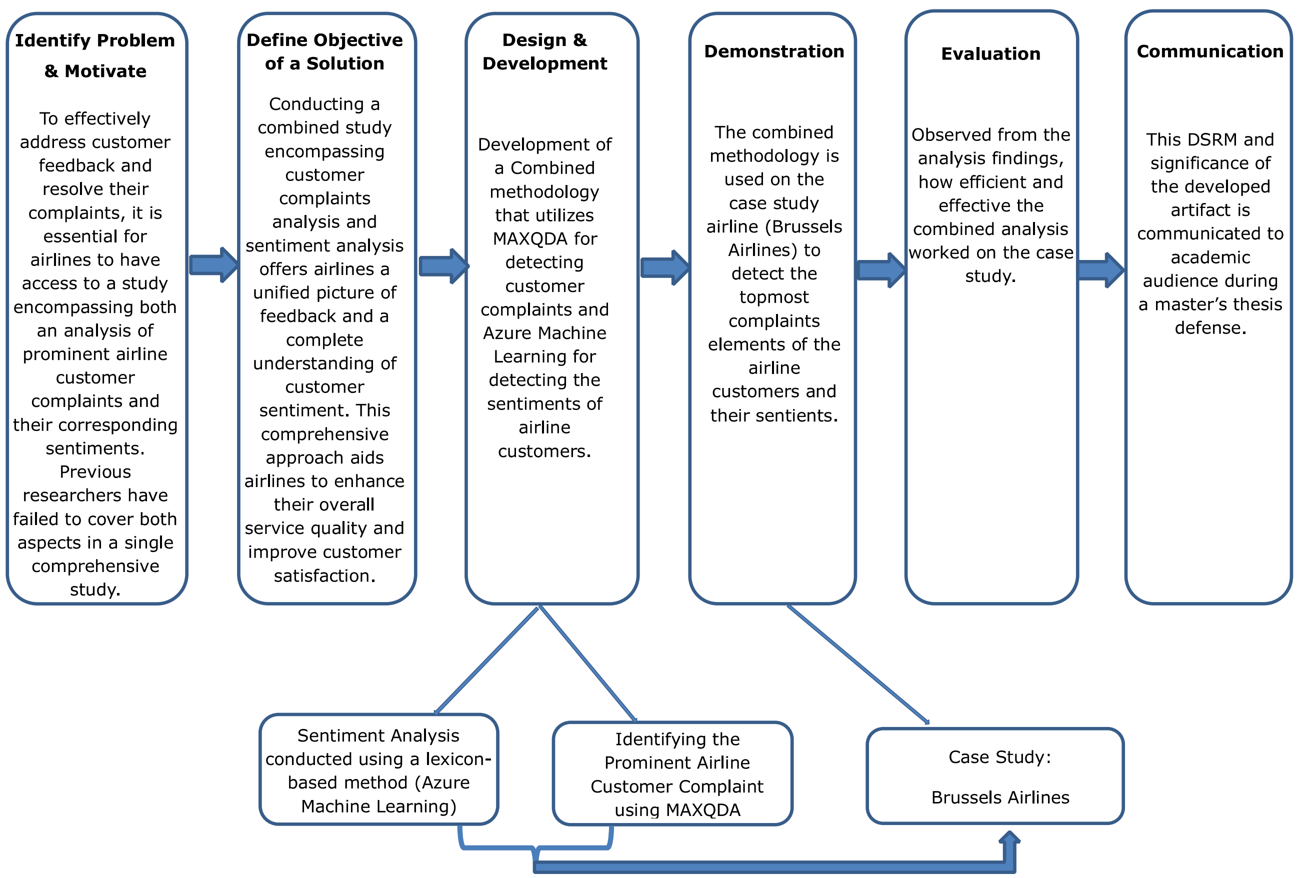


Figure 1. DSRM Approach of this study.

Activity 1. Problem Identification and Motivation: Defining the specific research problem and justifying the "value of a solution" is the first activity in the DSRM approach. It serves two purposes: it encourages the researcher and audience to investigate the answer further and indicates the researcher's comprehension of the problem (Peffers et al., 2008).

While previous research was relevant, it failed to offer airlines a complete understanding of customer complaints and customer sentiments. This study addresses a research gap in the airline industry by providing a comprehensive perspective on customer complaints and sentiment analysis in a single research paper. By providing this comprehensive perspective, the study serves as a valuable tool for airlines as it enables them to identify and promptly respond to customer complaints. Also, this broad perspective eliminates the need for airlines to engage in labor-intensive article scanning, looking for thorough knowledge.

Activity 2. Define the Objectives for a Solution: The objectives of a solution can be derived from the problem definition and an understanding of what is possible and feasible. These objectives may be qualitative, outlining how a new artifact can address problems that have not yet been examined, or quantitative, emphasizing measurable benefits over already available solutions (Peffers et al., 2008).

The objective in the context of this study is qualitative. The goal is to do a combined study of sentiment analysis and customer complaints within a single research paper, something which hasn't been done before. Using this innovative approach, airline firms may efficiently use customer feedback to recognize and comprehend customer concerns and sentiments, delivering considerable benefits.

Activity 3. Design and Development: Design and development, sometimes known as "creating the artifact," is the third activity in the DSRM approach, according to Peffers et al. (2008). This activity entails choosing the artifact's desired architecture and functionality before creating it.

The selected artifact in the context of this study is a method. This study specifically focuses on establishing a unified technique for analyzing customer complaints using MAXQDA and conducting sentiment analysis using Azure Machine Learning. This approach is designed to meet the study's stated goals: to give airlines a thorough grasp of customer feedback in a single research document. The method will consist of sentiment and customer complaint analysis components.

Activity 4. Demonstration: The fourth activity in the DSRM approach is demonstrating how to use the artifact. This demonstration can be done through various techniques, such as experimentation, simulation, case studies, proofs, prototypes, or other appropriate activities that demonstrate how the created artifact can be applied to solve real-world problems.

In this study, Brussels Airlines will be used as a case study to illustrate how the combined analysis approach is used in the airline industry. By applying the developed artifact to this case study, the study aims to showcase the artifacts' practical utility and effectiveness in addressing the identified research problem and establishing its potential value for other airlines in the industry.

Activity 5. Evaluation*:* As the fifth activity in the DSRM approaches, the evaluation activity starts once the application of the artifact to the case study is finished. The evaluation determines how well the artifact contributes to solving the noted problem by comparing the solution's objectives with the actual results obtained from applying the artifact. If the results are acceptable, the study moves on to the subsequent stage (Communication). However, if adjustments are required, the researchers may return to the design and development stage to improve the artifact's effectiveness or continue to the Communication stage and leave the improvement to be carried out by future researchers.

Based on the results of the artifact used on the case study, the performance of the artifact will be evaluated to gauge its effectiveness and to confirm if the study's aim was achieved.

Activity 6. Communication*:* The DSRM approach's final phase is communication, in which every aspect of the problem and the designed artifact are effectively shared with the relevant parties, such as academic audiences, stakeholders, and practicing professionals.

This master's thesis serves as the primary medium of communication. During the thesis defense, the findings, designed artifact, and general relevance of the research will be presented to the academic audience.

3.2.2 Data Collection

The information used in this study was gathered from TripAdvisor.com, a website where users may rate and comment on their experiences with different accommodation options, airlines, restaurants, and locations (Berezina et al., 2016). In this case, 2,259 user-generated Brussels Airlines reviews from TripAdvisor, spanning January 2017 to November 2022, were obtained for this study. Only reviews in English and those rated "average," "poor," and "terrible" were used as the data set for this study as they were thought to reflect the customer complaint aspects of Brussels Airlines services. The airline reviews, rating scores, and customer complaints are depicted in Figure 2 below.

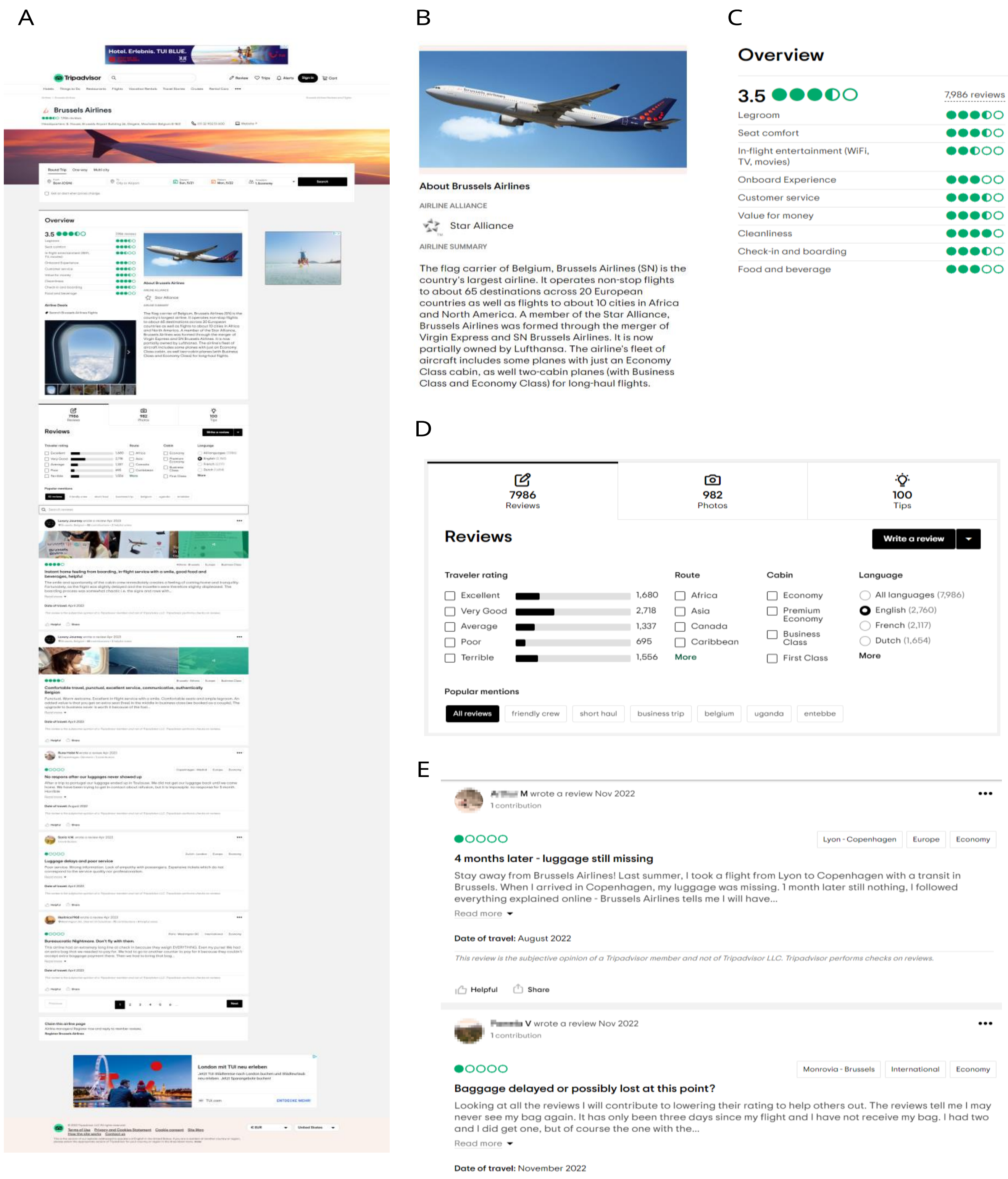


Figure 2: The TripAdvisor Brussel airline review and rating portal (Tripadvisor.com). ***Panel A**: The whole webpage of Brussels Airlines reviews on TripAdvisor**; B**: A summary of Brussels Airlines; **C**: An Overview of various aspects reviewed; **D**: Travelers Ratings; **E**: Examples of Customer Reviews about Brussels Airlines.*

3.2.3 Data Analysis

In line with the six steps of the Design Science Research Methodology (DSRM), a methodological artifact was employed to analyze customer feedback from Brussels Airlines. The artifact involved the combined analysis of customer complaints and sentiment analysis. All customer reviews were digitally coded and categorized using MAXQDA 2022, a qualitative data analysis software. This coding process aimed to identify the main topics or complaints (such as baggage loss, flight delay, and aircraft seating conditions) expressed by Brussels Airlines customers. Additionally, the software facilitated the identification of frequent patterns and themes (Denzin & Lincoln, 2011). Subsequently, sentiment analysis was conducted on the customer reviews using Azure Machine Learning. This analysis aimed to determine the overall sentiment expressed by Brussels Airlines customers regarding the services provided.

- **Data Analysis Using MAXQDA 2022**

MAXQDA is a qualitative data analysis software for qualitative and mixed-method data analysis (Creswell, 2014). This tool allows users to enter files such as interview transcripts, internet reviews, newspaper articles, Twitter tweets, and other data that will be analyzed. As soon as these files are imported, they are organized into document sets and assigned codes for several newly developing categories (Gregorio et al., 2014). The primary screen of MAXQDA has four windows that represent the main task areas involved in the analysis of qualitative data (Kuckartz, 2014). These windows are the Document System Window (which contains all of the project's text or data), the Code System Window (which provides the codes and categories' structure), the Document Browser Window (which displays the text currently being used), and the Retrieved Segments Window (for conducting searches and checks on coded material). Figure 3 below shows the various compartments of MAXQDA.

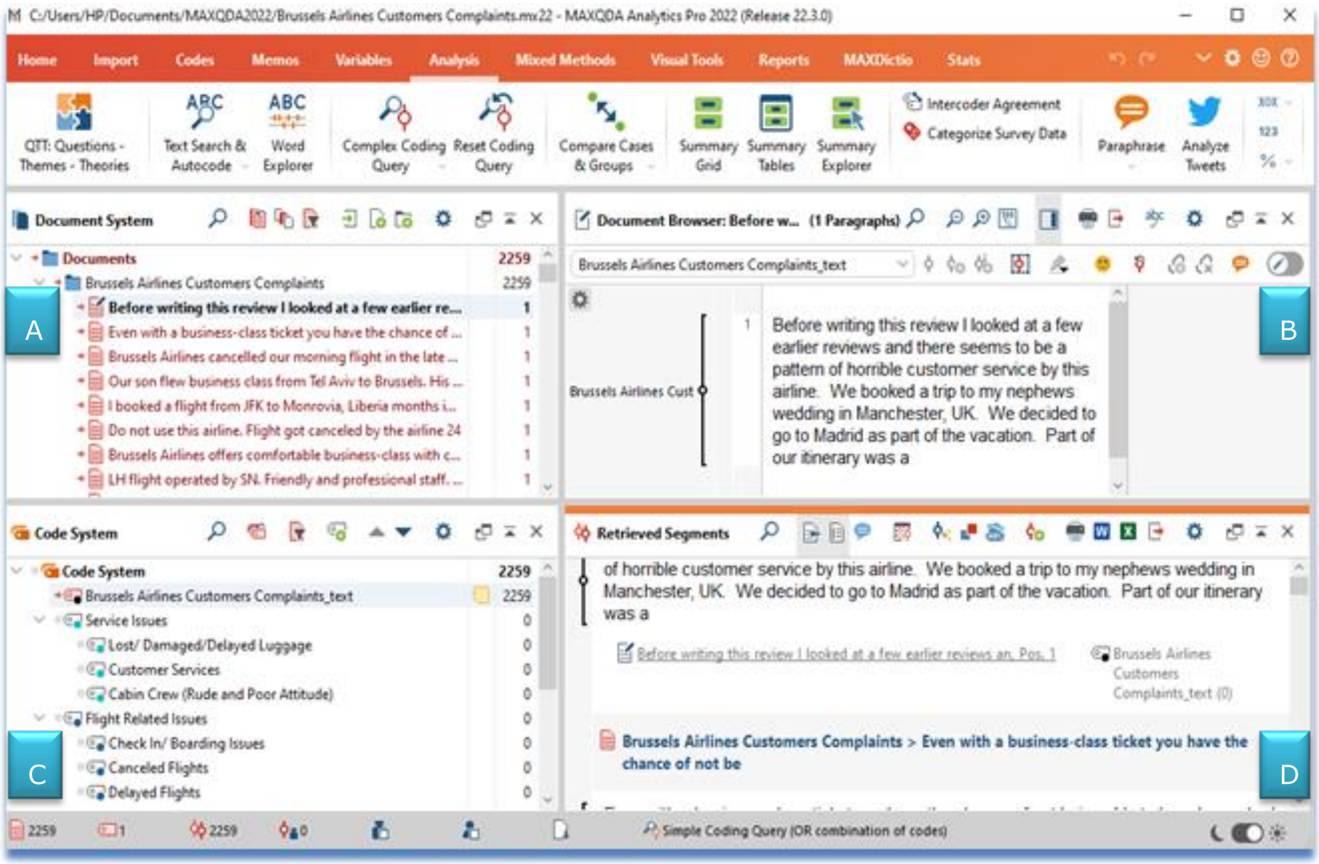


Figure.3 Overview of MAXDA Four Windows for Data Analysis. ***Window A****: Document Management Window,* ***B****: Overview of Document opened in A,* ***C****: Code System Window, and* ***D****: Retrieved Segment for the Overview of Coded Material from Window C.*

Data Coding with MAXQDA 2022

Coding in MAXQDA is simply assigning a code to a segment of data or a piece of data to a code (Ritchie et al.,2013). The user controls the creation of codes and categories in MAXQDA, which can be created before, during, or after the input data is analyzed (Braun & Clarke, 2006). As such, to categorize the reviews of airline customers into distinct complaint topics, I established various codes based on the readily available data. These created codes were afterward arranged in the MAXQDA's Code System windows in a hierarchical tree-like structure, enabling me to classify the data into various codes and sub-code levels. By selecting a review in the Document System Windows that showed up as an overview in the Document Browser Windows, I used a mouse to highlight the review portion containing a complaint, and I then added a code to the text. Alternatively, I coded the review section containing a complaint by dragging and dropping a pre-made code from the Code System Windows onto the text highlighted in the Document Browser window. Figure 4 below shows how manual coding appears in the document browser windows.

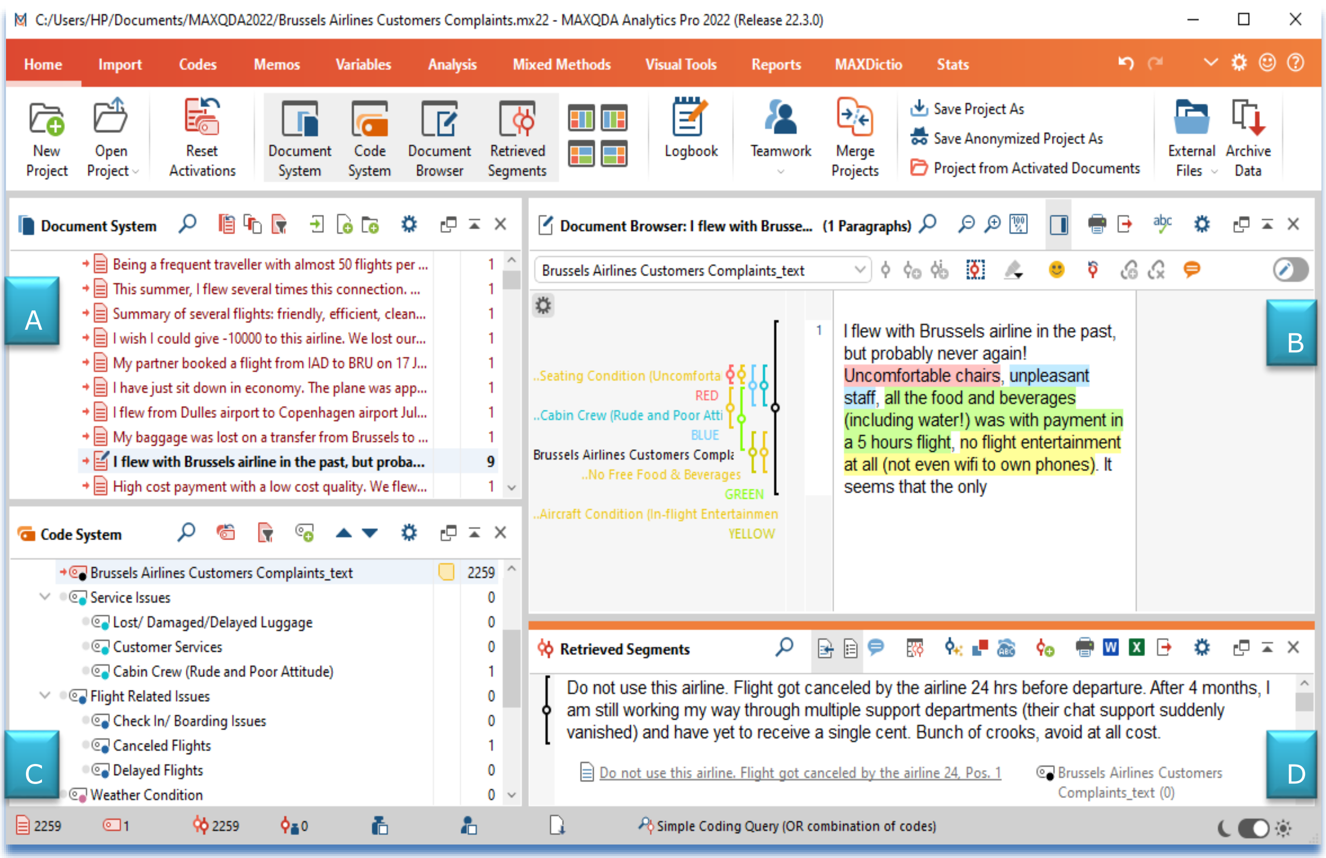
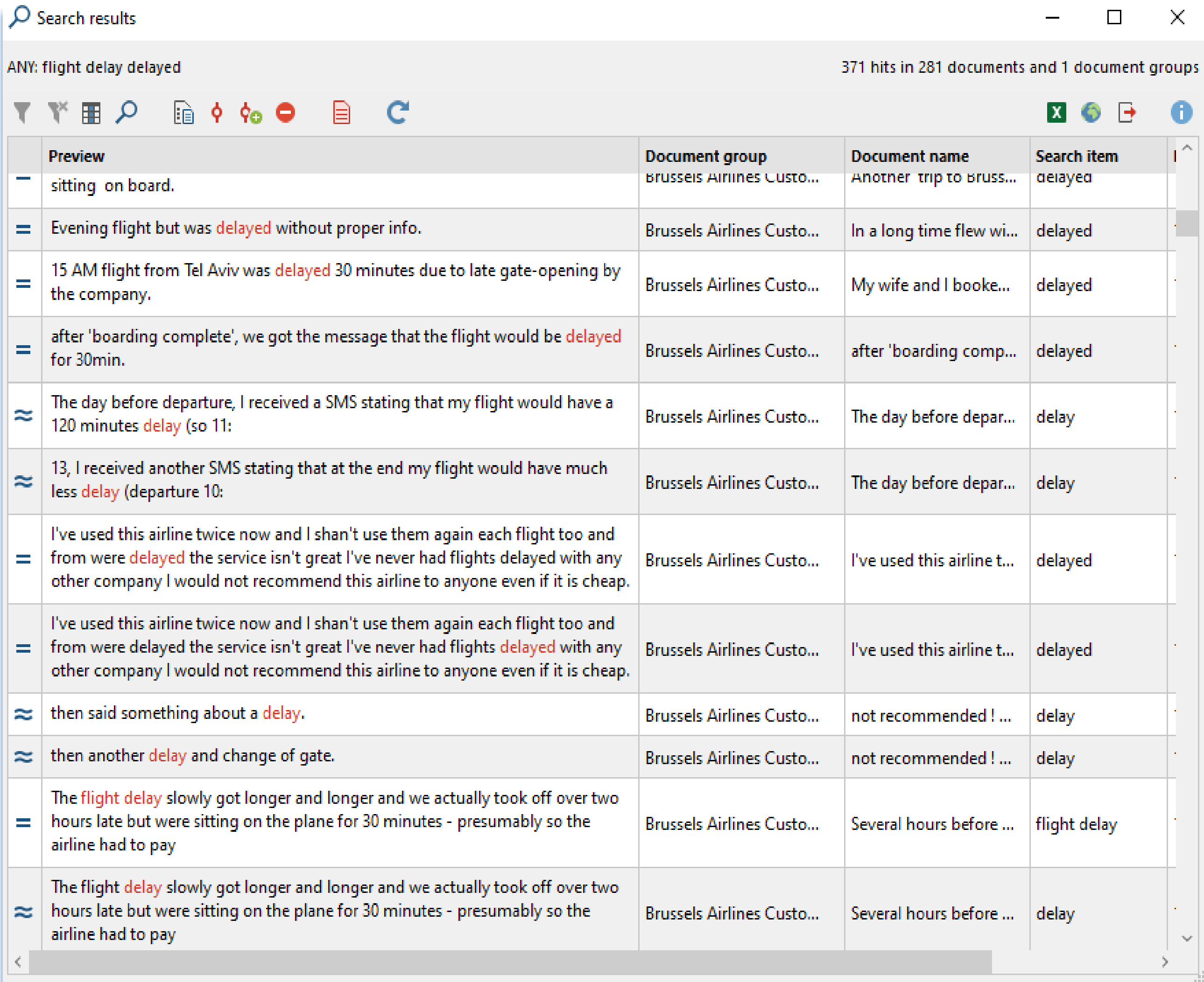


Figure. 4: MAXQDA Interface for Manual Coding. **Windows A**: *Document Management Windows,* ***B****: Overview of Document opened in A with Various Codes Assigned,* ***C****: Code Management System Windows,* ***D****: Retrieved Segment for the Overview of Coded Material from Windows C.*

In addition to the manual coding, the automatic coding feature provided by MAXQDA was used to enhance the coding process and achieve more accurate results. According to Colorado & Edel (2018), this auto-coding approach is entirely appropriate when qualitative data has been gathered in massive amounts, as in the case of the current study, because it allows for generating hundreds of code assignments simultaneously, saving time and effort. For auto-coding, the Word Cloud in the Retrieved Segment of the MAXQDA application was used not to create a visual representation of the analyzed data but to investigate the context of specific words that appeared within the analyzed data that could be further coded. A screenshot of the used Word Cloud is depicted in Figure 5 below.

Figure 5: A Word Cloud of Coded Segments collected in Retrieved Segments Windows of MAXQDA. *Words are displayed in different sizes based on their frequencies within the text. Examples of words frequently appearing in the reviews of the airline customers were flight, brussels, airlines, very, services, and time.*

By carrying out the auto coding, double-clicking on the word "delayed" in the Word Cloud, for instance, automatically resulted in the search term appearing within the retrieved segment, as illustrated in Fig. 6 below. The results obtained from the auto-coding were further coded to get a more comprehensive and detailed coding list.


Search results

ANY: flight delay delayed

371 hits in 281 documents and 1 document groups

	Preview	Document group	Document name	Search item
=	sitting on board.	Brussels Airlines Custo...	Another trip to Bruss...	delayed
=	Evening flight but was delayed without proper info.	Brussels Airlines Custo...	In a long time flew wi...	delayed
=	15 AM flight from Tel Aviv was delayed 30 minutes due to late gate-opening by the company.	Brussels Airlines Custo...	My wife and I booke...	delayed
=	after 'boarding complete', we got the message that the flight would be delayed for 30min.	Brussels Airlines Custo...	after 'boarding comp...	delayed
≈	The day before departure, I received a SMS stating that my flight would have a 120 minutes delay (so 11:	Brussels Airlines Custo...	The day before depar...	delay
≈	13, I received another SMS stating that at the end my flight would have much less delay (departure 10:	Brussels Airlines Custo...	The day before depar...	delay
=	I've used this airline twice now and I shan't use them again each flight too and from were delayed the service isn't great I've never had flights delayed with any other company I would not recommend this airline to anyone even if it is cheap.	Brussels Airlines Custo...	I've used this airline t...	delayed
=	I've used this airline twice now and I shan't use them again each flight too and from were delayed the service isn't great I've never had flights delayed with any other company I would not recommend this airline to anyone even if it is cheap.	Brussels Airlines Custo...	I've used this airline t...	delayed
≈	then said something about a delay.	Brussels Airlines Custo...	not recommended ! ...	delay
≈	then another delay and change of gate.	Brussels Airlines Custo...	not recommended ! ...	delay
=	The flight delay slowly got longer and longer and we actually took off over two hours late but were sitting on the plane for 30 minutes - presumably so the airline had to pay	Brussels Airlines Custo...	Several hours before ...	flight delay
≈	The flight delay slowly got longer and longer and we actually took off over two hours late but were sitting on the plane for 30 minutes - presumably so the airline had to pay	Brussels Airlines Custo...	Several hours before ...	delay

Figure 6: Automatic coding of search hits with new codes. *The word delayed is an example of a word searched from the word cloud for further coding.*

❖ **Data Analysis Using Sentiment Analysis**

After analyzing and coding the reviews to determine the prominent complaints of the airline customers, the next step in this study is to conduct sentiment analysis to determine the sentiments of the airline customers. Sentiment analysis is carried out in this study as a separate analysis using the lexicon-based approach. This sentiment classification approach is used instead of the machine learning approach because the machine learning approach, whose output depends on the data set's quantity and quality, requires a sizable training sample before it can be used. Also, the machine-learning approach is computationally intensive, time-consuming, and slower than the lexicon-based method due to the extensive data training (Chekima & Rayner, 2018; Augustyniak et al., 2016). In contrast, the lexicon-based approach is more convenient for this study because it is domain-independent, requires less time, is cost-free, and does not require a training and testing data set for sentiment classification (Taboada et al., 2011). Furthermore, Zhang et al., (2011) revealed that this approach is effective enough for text analysis at the document, phrase, and entity levels. Hence, due to the time constraints and because the current study is based on airline customer reviews, an example of a document classified at the document level of sentiment analysis, the lexicon-based approach is the best fit for this study.

Therefore, coupled with the simplicity and accuracy of the lexicon-based approach, the Azure Machine Learning tool was used to determine the sentiments of Brussels Airlines customers. This lexicon-based classifier was chosen for this study because of its ability to evaluate massive amounts of textual information, like internet reviews and news stories (Jelen, 2016). Also, it is cost-free and doesn't require coding expertise, unlike the other lexicon-based classifiers like SentiStrength and Vader, which require coding and programming knowledge of Python or Java to conduct sentiment analysis.

The Azure Machine Learning tool utilized in this study is available as an add-in for Microsoft Excel. This tool makes use of the Multi-Perspective Question Answering (MPQA) Subjectivity Lexicon (list of subjective clues), and this MPQA is mostly utilized in Microsoft Excel (Khoo & Johnkhan, 2018). Additionally, Khoo & Johnkhan (2018) revealed that the MPQA Subjectivity Lexicon functions as a general dictionary and has 8,222 sentiment analysis and opinion mining terms: 2,719 positive, 4,914 negative, and 591 neutral. Also, it includes all POS (parts of speech), such as adverbs, adjectives, nouns, and verbs (Khoo & Johnkhan, 2018).

The following procedures must be followed to conduct sentiment analysis on customer reviews and produce a more exact and reliable result. These steps include data collection, preprocessing, sentiment polarity identification, and Output presentation or visualization (D'Andrea et al., 2015).

A) Data Collection or Collection of User Reviews

To conduct sentiment analysis, customer reviews are required. In this regard, the TripAdvisor URL containing the airline reviews for Brussels was entered as input to the web scraper (Octoparse 8), after which a pagination loop (markings that show the order of the pages that will be scrapped) was created to extract every necessary data from the various pages of the websites. After completing the scraping process, the captured webpages were exported in CSV format, making them simpler to open in Excel. Once the text data was obtained, preprocessing was conducted to clean and prepare the data for sentiment analysis. This preprocessing involves removing the uninformative parts of the data, such as vague phrases, repetitions, poor terminology, and errors in language.

B) Data Preprocessing

Data preprocessing is the cleaning and preparing of gathered data for sentiment analysis categorization. Hemalatha et al., (2012) revealed that preprocessing is a crucial stage in the lexicon-based sentiment analysis technique. It is indeed a critical stage because unstructured data affects the outcomes of sentiment classification, and preprocessing the data gets rid of terms that aren't correct and streamlines the language used for sentiment analysis (Fernández-Gavilanes & et al., 2015). Data preprocessing involves the following steps: URL and punctuation marks removal, Spelling Correction, Filtering, Removal of Special Characters, and Stop Word Removal (Symeonidis et al., 2018).

- ***URL and Punctuation Marks Removal***

Since it is hard to accurately assess the sentiments of an online resource such as a web page, text, or image when linked to a URL, URLs are deleted in a text since they do not contribute to the sentiment of the text. Also, since some punctuations, like (.), (,), [], (...) frequently have little impact on the text's sentiment, these punctuations are eliminated before conducting sentiment analysis to improve the sentiment classification performance (Kim, 2018). In this study, punctuation marks like (.), (,), and [] were removed, but signs that signified the presence of emotions and feelings in a review, such as (!), (?), (" " or "'"), and emoticons or emojis, were left in place until the sentiment of the text was predicted. Furthermore, Symeonidis et al., (2018) revealed that removing certain punctuation marks and emojis may impact the accuracy of the sentiment classification.

- ***Spelling Correction***

Online users frequently make spelling mistakes in informal texts that could make sentiment categorization more difficult. It is feasible to increase categorization efficiency by utilizing tools that automatically rectify these mistakes (Mullen & Malouf, 2006). Although there is nothing like a flawless spelling checker, some spelling checkers, like Corrector, Grammarly, and Language Tool, offer success rates that are typically relatively high. For this study, Grammarly was utilized.

- ***Filtering***

People usually use repeated letters in words like 'exciteddddd' to express their feelings. However, because these words are not in the Azure Machine Learning tool, they were manually filtered out and replaced with their source word (excited). According to Mohammad et al., (2013), if these repeated letters attached to words are not filtered out, the classifier will classify them as different words. It won't consider them because of their uniqueness, especially when the repeated words are long.

- ***Removal of Special Characters***

To eliminate inconsistencies during the polarity classification, the study's data was manually inspected, and special characters like (*), (@), (#),($), and (%) were eliminated. If the special characters are not removed, they might occasionally be combined or linked with words, preventing these words from appearing in dictionaries.

- ***Stop Words Removal***

Stop word removal is a popular preprocessing step in sentiment analysis that includes deleting frequently occurring but meaningless words from text data (Pak & Patrick Paroubek, 2010). According to Haidar et al., (2018), stop word removal is intended to decrease the complexity of the text data so that the sentiment analysis algorithms may more effectively identify the pertinent words that contain sentiment information. The terms "the," "and" "of," and "in," among others, are examples of stop words that commonly appear in writing. These words must be eliminated from the data because they don't convey much sentiment information and are useless for sentiment analysis. In this study, MAXQDA was utilized to eliminate stop words such as "the," "and," "is," "for," "was," "on," "are," "be," and "as" from the airline customer reviews.

C) Sentiment Polarity Identification

After cleaning the retrieved data to make it suitable for sentiment classification, the next step is to extract the sentiment from the text and assign or classify the text with sentiment polarities (positive, negative, or neutral) using a sentiment analysis classifier (Pang & Lee, 2008). This study will use the Azure Machine Learning tool for sentiment classification.

D) Output Presentation or Visualization

Following the conducting of sentiment analysis to predict the sentiment polarity of the customer reviews, the next step is the presentation of sentiment classification results. This information can be presented in tables, pie charts, and bar graphs. The study's section 4.2 provides an overview of the sentiment analysis results.

➢ ***Data Analysis with the Lexicon-Based Tool (Azure Machine Learning)***

Sentiment analysis can be conducted when the data has been appropriately cleaned, guaranteeing satisfactory outcomes. With Microsoft Azure Machine Learning, the subsequent steps need to be considered to execute sentiment analysis:

- The computer or laptop must have a copy of Microsoft Office 13 or above installed.
- After launching Microsoft Excel, an add-in for Azure Machine Learning is installed.
- After that, the installation of a Web Service called Text Sentiment Analysis Excel Add-in sample follows.
- Import the cleaned and prepared data to be analyzed.
- Next, the column header containing the customer reviews of Brussels Airlines must be modified to "tweet text" because that is how it is input in the schema.
- Following that, the Excel sheet's input and output columns are defined.

- After defining the input and output columns, click "Predict " for the sentiments of the reviews to be predicted.

Screenshots of the analysis procedure are depicted in the figures below for a better understanding. Figure 7 displays the customer reviews of Brussels Airlines complaints extracted from TripAdvisor and imported into Excel.

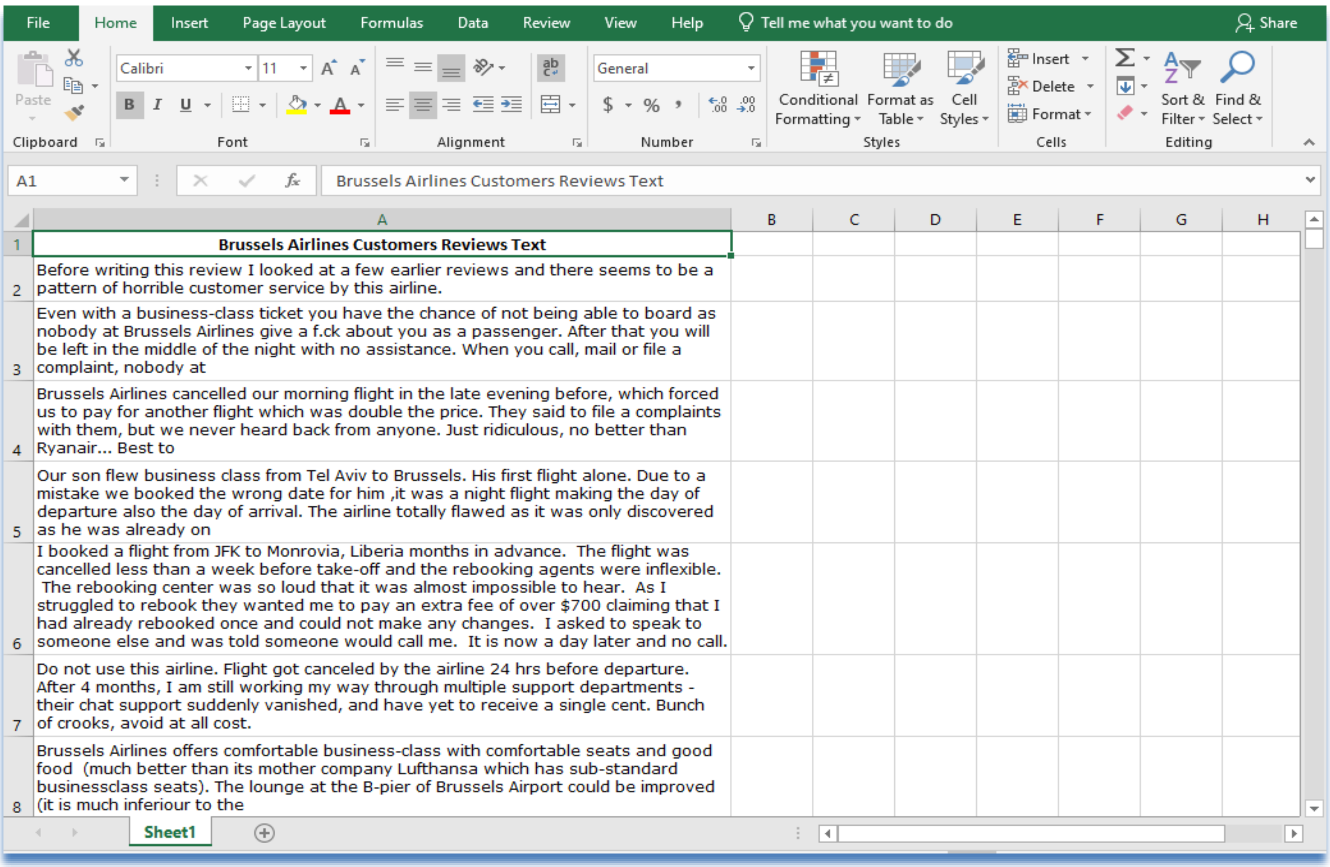


Figure 7. Brussels Airlines Customer's Reviews from TripAdvisor. *Customer reviews were captured in Excel for onward analysis.*

The header of the column containing customer reviews must therefore be changed from "Brussels Airlines customers review text" to "tweet_text," as the Azure machine learning schema only accepts that string in "tweet_text." Figure 8 below depicts this form.

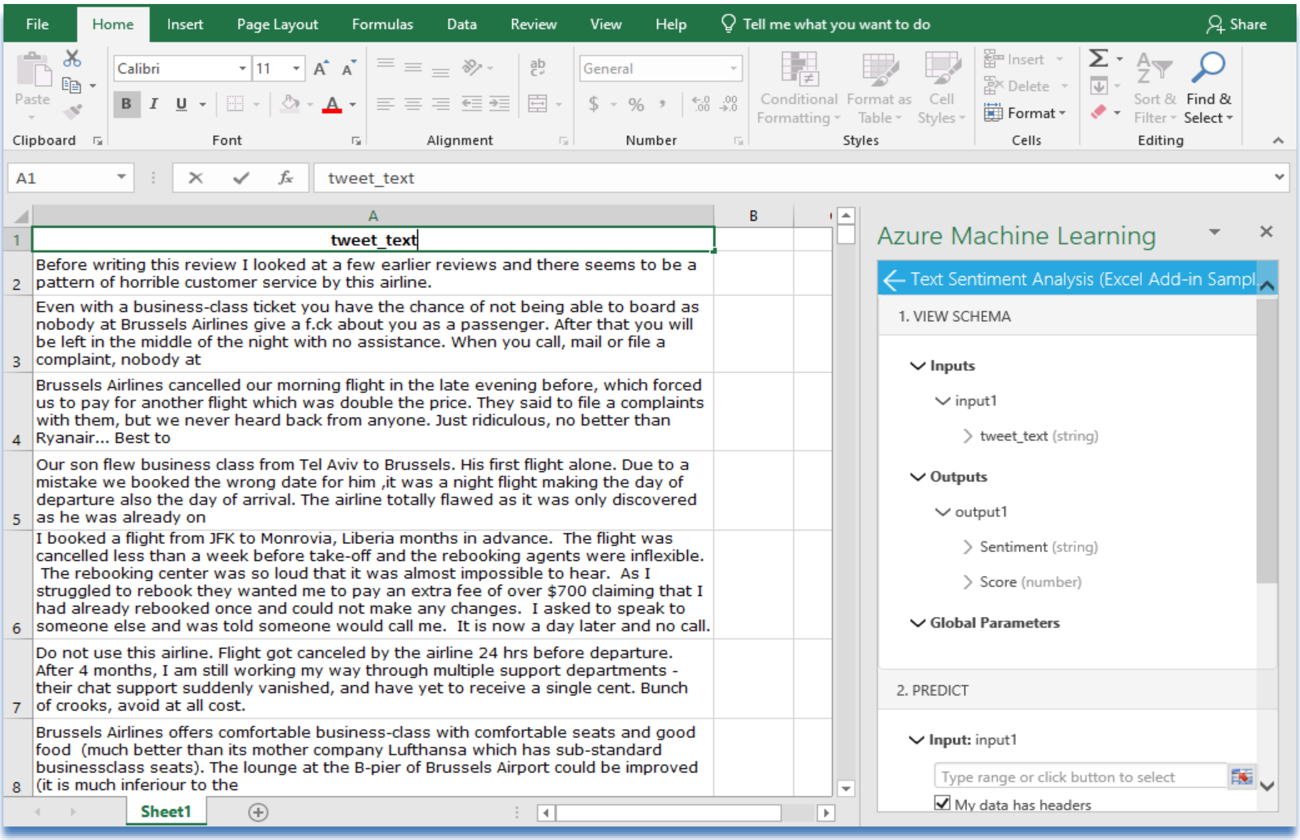


Figure 8. Modification of text header for Classification. *Azure Machine Learning add-in on Microsoft Excel is used for sentiment analysis prediction.*

After modifying the header, the input and output columns are then defined. Using the Azure Machine Learning (Test Sentiment Analysis add-in on Microsoft Excel), the reviews are predicted to detect the sentiments of airline customers. This prediction is shown in Figure 9 below.

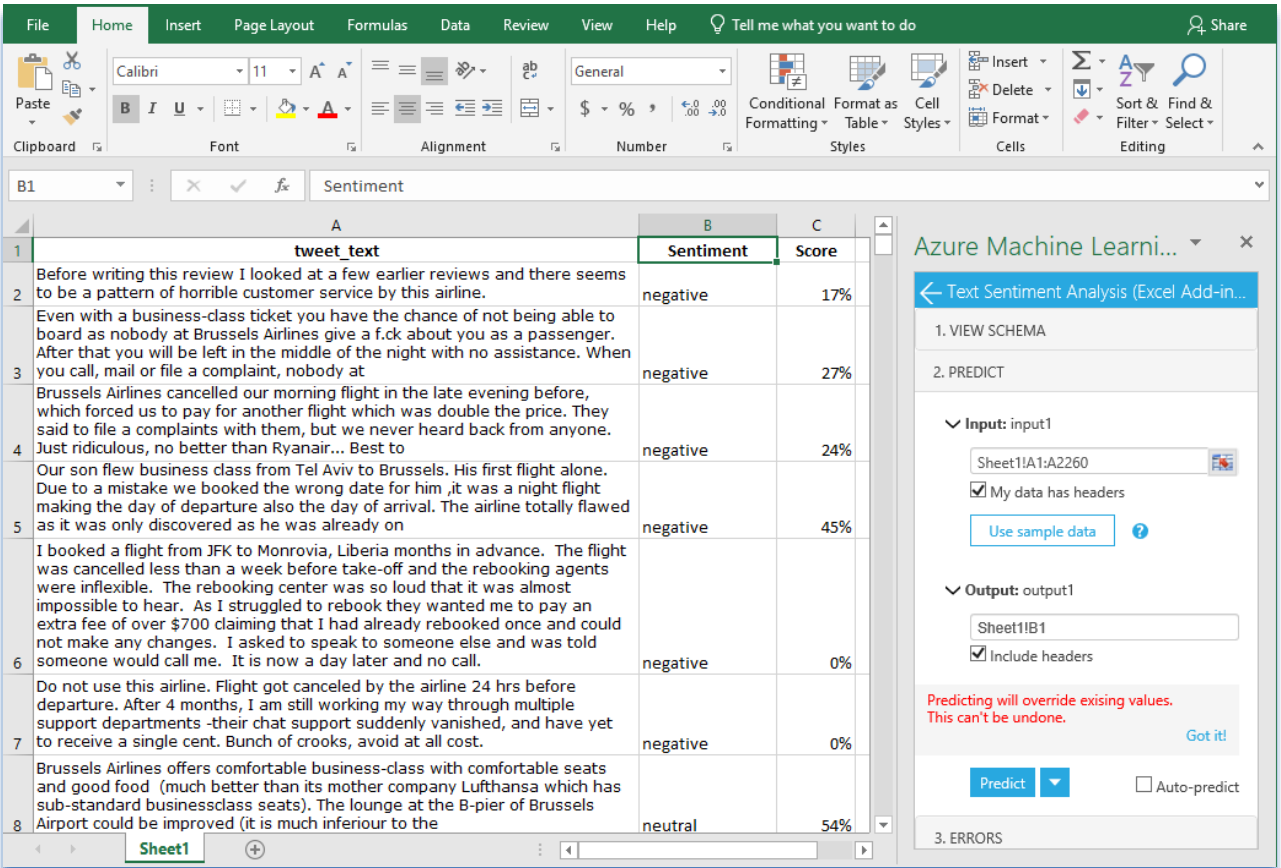


Figure 9: Outcome of Sentiment Analysis using Azure Machine Learning. *Sentiment polarity (negative, neutral, and positive) and score predicted.*

4 RESULTS

This section of the study presents the analysis results in the abovementioned section. The results of the analysis carried out on MAXQDA to determine the various Brussels Airline customer complaints are presented in Section (4.1), and that of sentiment analysis to determine the airline customers' sentiments towards their services is presented in Section (4.2).

4.1 Results of the MAXQDA Analysis of Customer Complaints of Brussels Airlines

After the manual and automatic coding of the customer reviews, as depicted in Figs. 4 and 6 above, the data was subjected to a Code Frequency analysis to determine the distribution and frequency of codes in the various coded segments. Since most Brussels Airlines' customers complained about several topics in their reviews, the frequency totals for each theme were higher than the overall number of reviews evaluated. The analysis of the code frequency resulted in a table that provided a clear split of the number of complaints, their frequencies, and percentages. These major airline complaints and their frequencies are shown in Table 1 below.

Table 1: Prominent Customer Complaint Types, Frequencies, and Percentages Regarding Brussels Airline. *Top complaints based on frequencies include customer luggage, check-in/boarding, and canceled flights.*

Prominent Complaint Topics	**Number of Complaints**	**Percentage of Complaints**	**Frequency of Occurrence of Complaints**	**Percentage of Frequency**
Customer Services	185	10.5	196	5.6
Lost/Damaged/Delayed Luggage	410	23.3	670	20.2
Cabin Crew (Rude and Poor Attitude)	227	15.7	317	9.5
Flight Delays	311	17.7	347	10.4
Check-In/ Boarding Issues	449	25.5	574	17.3
Canceled Flights	159	9.0	409	12.3
Poor Weather Condition	22	1.2	27	0.8
No Refunds & Compensation	95	5.4	121	3.6
Aircraft Condition (In-flight Entertainment)	81	4.6	86	2.6
Seating Condition (Uncomfortable and Narrow)	224	12.7	246	7.4
Food & Beverages(Poor Quality or No Free)	297	16.9	331	10.0
Total	**2510**	**100**	**3324**	**100**

4.1.1 Luggage-Related Issue (Lost/ Damaged/ Delayed Luggage)

According to the information in Table 1, it is clear that a substantial portion of complaints from Brussels Airlines customers was about problems with delayed, damaged, and missing luggage, which accounted for 670 (20%) of total complaints. Both domestic and international airline customers reported these complaints upon their arrival at their destination, and these customers voiced their displeasure with the airline's services through various reviews, highlighting their unpleasant experiences with luggage handling. Here are some customer reviews concerning their luggage:

"We flew from Tel Aviv airport to JFK with a stopover in Brussels. On arrival at JFK, one of our suitcases had not arrived. It's 4 weeks now, and after many phone calls to their customer service number, a Belgium number, horrible service, telling us to file claims on their website. So far, nothing v found. And no refund

either. I have a name on my suitcase. I have a luggage tag, don't know why they can't locate the suitcase. It seems like no one cares."

"Searching for a nightmare flight? You should definitely go with Brussels Airlines. Luggage lost, never given any update, customer support completely incompetent, never received any reply to my claims. Lost valuable things + had to buy new ones. Luggage can get lost, but how Brussels Airlines handles this is awful and very deceiving. Horrible experience!"

4.1.2 Flight-Related Issues (Check-In and Boarding, Canceled and Delayed Flights)

After luggage-related issues, Brussels Airlines faced a considerable number of complaints about flight-related issues. Checking and Boarding Issues, Canceled Flights, and Delayed Flights were the second, third, and fourth most common grievances, accounting for 574(17%), 409(12%), and 347(10%) of all complaints, respectively. The airline customers expressed dissatisfaction with the lack of information and explanations for flight delays or cancellations. They also reported encountering slow-moving, rude, and unprofessional airline staff during check-in and boarding, leading to chaotic situations. The few examples of customer reviews below highlight customers expressing their displeasure with the airlines regarding these flight-related issues.

***Check-In**: "The worst and most unfriendly check-in I've had so far at an airport. The Check-in only opened 1 hour before boarding. In the end, we managed to get to the gate right when boarding started. Also, the employees were not helpful and very impolite."*

***Flight Boarding**: "We - a family of five - took a round trip to Mumbai from Brussels. SN601 flight to Mumbai on December 9 was okay. The boarding process was rather chaotic, with poor instructions on how sequential boarding is to be done. The in-flight entertainment system is poor."*

***Canceled Flight**: "Do not use this airline. Flight got canceled by Brussels airline 24 hrs before departure. After 4 months, I am still working my way through multiple support departments (their chat support suddenly vanished) and have yet to receive a single cent. Bunch of crooks, avoid at all costs".*

***Delayed Flights**: "4 weeks, no response from Brussels Airlines! 2207-SN-01870 In Brussels, our flight was delayed for 3 hours; during that time, we were bounced around between multiple gates with no updates being given unless asked."*

4.1.3 Food and Beverages

Following flight-related difficulties, the fifth component that airline customers complained about the most was Food & Beverage. Some customers of Brussels Airlines complained about the food's poor and unpleasant quality and also mentioned that they had to pay for meals because nothing was provided for free. This complaint category accounted for 10% of the total complaint with a frequency value of 331. The following are some examples of airline customer reviews about food and beverages.

No Free Food nor Beverages: *"I flew with Brussels airline in the past, but probably never again! Uncomfortable chairs, unpleasant staff, all the food and beverages (including water!) were with payment in a 5 hours flight, no flight entertainment at all (not even wifi to own phones). It seems that the only thing the staff cared about was selling food."*

Food Quality: *"Four traveling to Budapest via Brussels. The seat in front of me was literally touching my knees, and I am only 5'11". The food was horrible. Mashed potatoes with the chicken were like under-cooked grits with butter, and some industrial chemical applied."*

4.1.4 Service-Related Issues (*Cabin Crew and Customer Service*)

In addition to the aforementioned issues, Cabin Crew and Customer Service were also issues expressed by Brussels Airlines customers, according to Table 1. Cabin Crew complaints accounted for 317 (10%), the sixth complaint component, while Customer Service, the seventh complaint component, constituted 196 (6%). According to customer reviews, the airline's customer care personnel lacked good communication skills, resulting in long phone wait times and an unfriendly and disrespectful attitude. Customers also complained about unhelpful and unpleasant cabin crew behavior during flights. These service-related concerns led to a lack of customer satisfaction, prompting customers to complain, as seen in a few examples of airline reviews below:

Cabin Crew: *"On the way to Belgium, there was a couple with 2 toddlers, one of whom got sick a few hours into the flight. The air steward was rude, belligerent, and downright aggressive toward the family when the little girl vomited. She forced one of the parents to clean up the mess and leave the child. On the way back, my suitcase was lost. They were apathetic at best."*

Customer Services: *"The absolute worst airline I've ever encountered. They have the worst customer service and did not help at all when my flight was canceled. I spoke with 5-6 different people, and none cared to book me on another flight. I missed my sister's wedding as well as 3 connecting flights for my trip. Giving them a 0 for a review would be generous. I will never be using this airline, and I'll also tell all my friends and family about this experience."*

4.1.5 Physical Aspects (*Seating Conditions and Aircraft Condition*)

Seating conditions onboard Brussels Airlines aircraft and the overall condition of the aircraft were also key complaints cited by the airline customers in their reviews. The Seating condition was the eighth complained component, accounting for 246 (7%) of all complaints, while the general aircraft condition, the ninth complaint issue, accounted for 86 (3%). Customers were dissatisfied with dirty planes, unpleasant seats (cramped seating and limited legroom), and a lack of in-flight entertainment options. Below are a few examples of these customers expressing dissatisfaction with seats and aircraft conditions.

Seating Condition*: "I flew from Dulles International Airport to Brussels and from Brussels to Prague. The seats on the airplane were the most uncomfortable I have ever sat in. The bottom was thin & I felt like I was sitting on a wood plank."*

Airline's Aircraft Condition*: "I have just sat in the economy. The plane was apparently not cleaned after the previous flight. Dirty seats in the whole row. Is this really a quality-of-service Star Alliance member should provide?"*

In-flight Entertainment: *"There was no in-flight entertainment or power outlets to charge devices. So, if you decide to fly with Brussels Airlines, pack a lunch, fill your water bottle once you're through security, and ensure your device is fully charged."*

4.1.6 No Refunds and Compensation

Following complaints about the physical component, airline customers also raised issues with refunds and compensation. These airline customers complained about not getting refunds or compensation for their canceled flights. The frequency of this complaint component was 121 (4%), and it was the tenth complaint component. Listed below are a few comments made by customers of Brussels Airlines regarding the issue of no refunds and compensations they didn't receive after a flight cancelation or lost luggage.

No Refunds: *"After our flight was canceled an hour before we were supposed to depart, a staff member reassured us that Brussels Airlines would reimburse us for hotel costs, etc. After making a claim in January and writing two follow-up emails kindly requesting a response, I have heard nothing. It was our first and probably last time we traveled with Brussels Airlines."*

No Compensation: *"This airline is a complete and utter mess. They canceled my flight with no date. Customer service is a lousy call center in India that is lying and has no competence whatsoever. They have overbooked my flight and are unwilling to give any compensation or refund."*

4.1.7 Poor Weather Conditions

The last and least frequent topic for customer complaints was unfavorable weather, which had a remarkably low-frequency value of 27, accounting for only 1% of the total complaints. According to some airline customers' reviews, most airline customers that mentioned this complaint component acknowledged that the weather conditions were out of the airlines' control and that it was not their fault that they were in that situation. The following is an example of an airline customer's review regarding the weather condition aspect:

"The flight was canceled due to bad weather, no fault of the airline. After waiting several hours on the runway, we were refused takeoff. Then the captain informed us that the onboard staff could not do any extra hours and we would have to return to the terminal!"

4.2 Results of Sentiment Analysis

As depicted in Fig 9 above, sentiment analysis was carried out to determine the sentiments of Brussels Airlines customers towards their services. The analysis results are displayed using a pie chart shown in Figure 10 below to make the sentiment distribution and proportions in the studied data simple to comprehend.

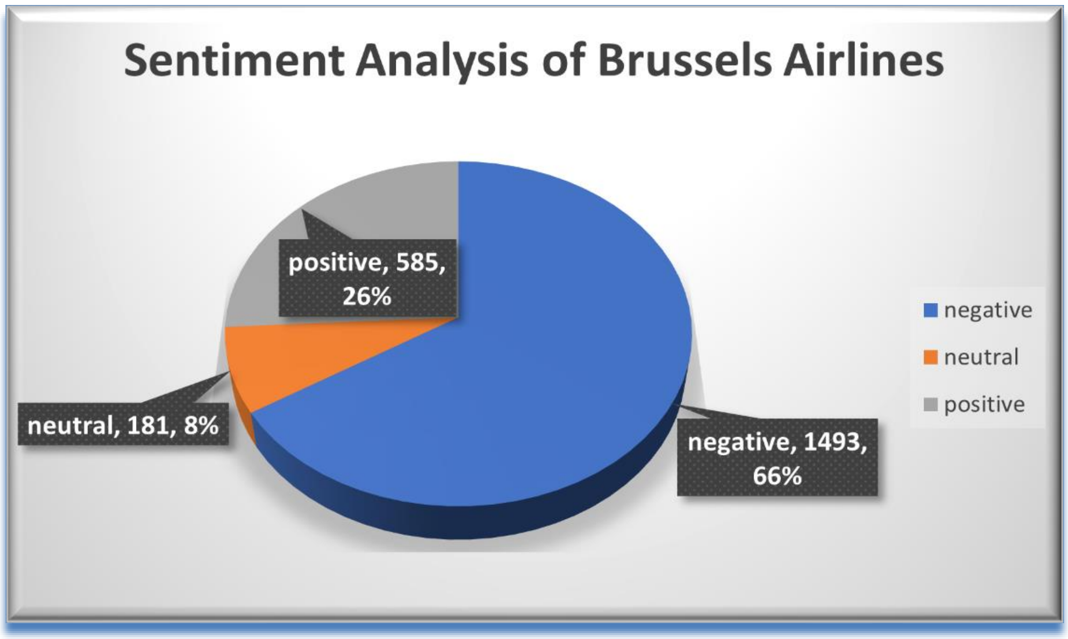


Figure 10. Results of Sentiment Analysis. *Negative sentiments are highest (66%), while neutral is lowest (8%). The raw data used for generating the pie chart is in the appendix.*

According to the findings depicted in Figure 10, out of the 2259 TripAdvisor reviews of Brussels Airlines customers that were rated "average," "poor," and "terrible" and were written in English, (66%) of those customers had negative sentiments about the airline's services, (26%) felt positive, and only (8%) felt indifferent or neutral. Using MAXQDA, a frequency analysis was subsequently conducted to discover the most prevalent words or phrases used in the studied data, as these words were frequently connected with sentiments. According to Kuckartz & Rädiker's (2019) studies, MAXQDA can identify the top word frequencies and the terms most used in combination with other words in an in-text analysis. The results of the frequency analysis are displayed in Table 2 below.

Table 2: Results of Frequency Analysis using MAXQDA. *Examples of words that appeared more frequently in the customers' reviews of Brussels Airlines are flight, brussels, airlines, very, services, etc.*

Rank	Word	Frequency	Rank	Word	Frequency	Rank	Word	Frequency
1	flight	1747	41	cabin	131	82	free	76
2	brussels	1261	41	short	131	84	lost	75
3	airlines	684	43	pay	130	84	made	75
4	very	678	44	Company	128	86	quite	74
5	service	652	45	Customer	126	87	paid	72
6	time	585	46	delay	122	88	attendants	70
7	good	523	46	took	122	88	waiting	70
8	airline	479	48	arrived	121	90	connection	69
9	food	350	51	trip	117	90	departure	69
10	staff	319	52	Canceled	116	92	entertainment	68
11	flights	311	53	price	115	93	online	67
12	airport	306	53	take	115	94	legroom	66
13	plane	306	55	water	111	94	refund	66
14	seats	276	53	return	108	96	asked	65
15	only	273	57	drinks	105	96	pleasant	65

16	luggage	256	58	long	104	98	problem	64
17	friendly	253	58	minutes	104	99	full	63
18	crew	222	58	room	104	100	airplane	62
19	seat	212	61	clean	103	100	drink	62
20	check	207	61	people	103	102	booking	61
21	back	193	63	bad	101	102	fine	61
22	boarding	190	64	check-in	97	104	efficient	60
23	experience	188	65	cost	96	104	money	60
24	comfortable	187	66	passengers	93	106	planes	58
25	hours	178	66	space	93	107	tickets	57
26	great	172	66	told	93	112	information	55
27	class	167	69	Excellent	90	114	find	54
28	business	166	70	travel	89	116	meal	53
29	flying	164	71	extra	86	116	terrible	53
30	booked	161	71	helpful	86	116	used	53
31	late	157	73	small	85	121	bags	52
32	board	156	74	left	83	121	europe	52

33	delayed	151	75	aircraft	82
33	never	151	75	same	82
33	nice	151	77	better	79
36	flew	145	78	Baggage	78
37	leg	142	78	connecting	78
38	again	140	78	smooth	78
38	economy	140	78	worst	78
40	hour	135	82	ever	76

Table 2 above presents the top 121 terms that appeared most frequently in customer reviews for Brussels Airlines. Some of the keywords that expressed negative feelings or attitudes included "late," "delayed," "waiting," "never," "canceled," "bad," "worst," "lost," "problem," and "terrible." The airline customers often used these words when they experienced service breakdowns or flight delays, causing distress, particularly for those who may have missed connecting flights or important events. Simar to the negative words, words like "good," "friendly," "great," "excellent," "helpful," "smooth," and "pleasant" were used to express positive feelings and satisfaction. The airline customers used these words to describe a degree of satisfaction. For instance, the term "friendly" was used when the airline customers were pleased with the courtesy and welcoming attitude of the flight attendants on board. Finally, there were neutral terms such as "fine," "same," "made," "small," and "quiet." For instance, customers may have used "small" to describe the aircraft's seat size or available legroom.

5 DISCUSSION

This section discusses and explains the findings, the overall limitations, and managerial implications. The discussion of the results, limitations, and managerial implications are covered in Sections 5.1, 5.2, and 5.3, respectively.

5.1 Discussion Of Results

This study analyzed 2,259 TripAdvisor reviews of Brussels Airlines, specifically those rated "average," "poor," and "terrible," written in English to identify the most common complaints and customer sentiments. The study found that the top complaint was luggage-related, with customers expressing dissatisfaction for their delayed, lost, or damaged luggage. Other frequent complaints included flight delays and cancellations, insufficient information from staff, and unprofessional behavior during check-in and boarding. Customers also expressed dissatisfaction with customer service and the attitude of cabin crew members. Physical factors such as food and beverages, seating conditions, aircraft cleanliness, and entertainment were also mentioned as sources of complaint. Also, sentiment analysis was conducted to identify the customers' feelings towards the airline's services, and the results revealed that most reviews of the airline customers were negative, implying that these customers felt unhappy with the airline's services.

The outcome of this study also highlights the relevance of using the Design Science Research Methodology (DSRM) proposed by Peffers et al., (2008) as a means to generate innovative ideas in the form of designed artifacts (methods, models, procedures, and instantiations) to resolve real-world and organizational problems. The Evaluation, which constitutes the fifth activity in the Design Science Research Methodology, validates explicitly the success of the study's designed artifact (a method that combines customer complaint analysis and sentiment analysis) in solving the study’s research problem and accomplishing the study's goals. The information in this single study would give airlines a comprehensive understanding of using their customers' feedback to identify specific development areas. It will save airlines the time and effort of reading multiple articles online to understand how they can know of their customers' complaints and their sentiments towards their services. Lastly, this study will assist airlines such as Brussels Airlines to promptly make strategic decisions that will rapidly address customer complaints, improve overall service quality and happiness, and increase customer loyalty and competitiveness in the airline market.

5.2 Limitations

In the course of performing this study, several limitations were noted. The first limitation of the study was that it only examined TripAdvisor reviews written by customers of Brussels Airlines in English, excluding the opinions and potential complaints of other airline customers who posted reviews in other languages. Analyzing the reviews of the other airline customers written in different languages would have produced additional insights into the customers’ complaints and the sentiments of the airline customers.

Secondly, because TripAdvisor was the primary data-gathering platform, this study's results were restricted to that single website or social media platform.

Lastly, data on some of the demographic characteristics of airline customers (such as gender, age, and educational background) was unavailable as it wasn’t mentioned in the reviews. Including these variables in the analysis would have produced more significant insights.

5.3 Managerial Implications

It is practically apparent that service providers like airlines will inevitably experience specific service issues during business operations, leading to customer complaints. Hence, to reduce the impact, the management of an airline like Brussels Airlines should determine the causes of the service failure and the extent to which these failures affect customer satisfaction. Based on the findings of this study, the top complaints that the airlines should focus on are those related to the customer's luggage, flight-related issues(check-in/boarding and flight cancelation), and the quality of customer services rendered to the airline customers (on-ground and on-board).

In order to limit these service failures, Brussels Airlines management should concentrate on streamlining operational activities to reduce service failure. The management should focus on regular maintenance and monitoring of all daily operational activities and facilities, both on-ground and on-board, such as routine aircraft inspection and maintenance, optimizing flight schedules to reduce delays or cancellations, and monitoring the baggage handling area. The constant maintenance and monitoring of these aspects can assist in identifying problems beforehand and mitigating their effects.

In circumstances where delays or other service failures are unavoidable, the airline managers must devise communication techniques such as hiring responsive workers with good communication skills competent enough to address the severity of service failures. Training and skill development programs should also be implemented regularly to enhance workers' communication skills and provide them with the knowledge to properly understand and politely resolve customer complaints. After acquiring the required skills from the training and development program, the customer service personnel should be given the authority by their managers to handle customer complaints promptly. By so doing, the waiting time occasionally caused by staff members waiting for their supervisor's feedback or approval on how to address a service problem will be significantly reduced. Additionally, The swift response to customer complaints will decrease the severity and negative repercussions of a service failure and positively impact customers' sentiments towards the airlines, likewise their loyalty and satisfaction.

In addition to improving communication, effective employee performance should be monitored and rewarded because happy employees will lead to satisfied customers (Zeithaml et al., 2013). Also, it is essential to keep customers informed about the nature and extent of the service breakdown and what is being done to fix it. By doing this, the airline may ease customers' worries and give them the impression that they are sincere and making every effort to remedy the situation. Studies by (Anderson et al., 2009) also suggest that doing this can increase customers' pleasant feelings while lowering their negative ones.

Lastly, the airline should initiate effective procedures to get quantitative and qualitative feedback from their customers by encouraging them to provide it at various stages (either during pre-boarding or seating in the passenger waiting area, in-flight and post-boarding). This input can be utilized to quickly comprehend the potential causes of service failure.

6 CONCLUSION

In conclusion, this study employed the Design Science Research Methodology approach to develop a methodological artifact that combined the analysis of customer complaints and sentiment analysis. The artifact was applied to Brussels Airlines, which served as the case study for this study, aiming to determine the most prominent complaints made by airline customers as well as their sentiments towards the airline services. Based on the study's findings, it's indeed apparent that Brussels Airlines customers are dealing with various problems that negatively affect their overall happiness with the airline's services. These problems include luggage handling, check-in and boarding issues, flight delay and cancellation issues, poor customer service, weather conditions, and other physical issues, such as the state of the aircraft (cleanliness and in-flight entertainment). Therefore, It is essential for airlines like Brussels Airlines to successfully handle these issues if they want to elevate their position and reputation in the fiercely competitive airline market. By addressing these problems, the airline can improve customer satisfaction levels by addressing these problems, encouraging customer loyalty, raising repurchase intentions, and producing favorable online reviews and word-of-mouth recommendations.

6.1 RECOMMENDATIONS

The study's findings on customer complaints and sentiment analysis on Brussels Airlines reveal various areas for development. Flight delays, cancellations, and boarding issues were highlighted as common complaints, prompting the airline to investigate the core reasons. To reduce the inconvenience caused by delays or cancellations, the study suggests providing customers with updated flight information, offering rebooking choices, prioritizing safety, and paying compensation where necessary. Using an online airline booking system as a control mechanism can also aid in identifying and reducing errors, resulting in increased operational efficiency.

In response to complaints about mishandled luggage, the study suggests installing solutions such as an online tracking system that provides airline customers with a tracking number to check the status and location of their luggage. To ensure proper handling of customers' luggage, training programs should be implemented for luggage handlers, highlighting the importance of careful handling. Installing surveillance cameras in the luggage area can also aid in monitoring and holding handlers accountable for mishandling incidents, facilitating appropriate action when necessary. By applying these ideas, Brussels Airlines may improve customer happiness and overall service quality and effectively compete in the airline market.

Lastly, regarding seating conditions, in-flight entertainment, and food quality, the study recommended that Brussels Airlines consider updating its aircraft seats to meet customer expectations. The seat comfort can be improved by increasing the leg room and using softer cushions. To improve the meal experience, the airline should offer a diverse selection of high-quality and reasonably priced food. Again, it is recommended that the airlines make every effort to be more innovative and boost in-flight entertainment by giving intriguing elements such as a variety of documentaries, short movies, games, and music. Customers may also be allowed to pre-select a film or documentary for free or at a low cost when booking seats online.

6.2 FUTURE RESEARCH

This study had a few limitations mentioned above that could be addressed in the future. Future research could use other online platforms like Skytrax, Twitter, and Facebook as different sources for data collection without filtering the language variable. Future researchers may also use additional data-gathering techniques, such as interviews and surveys, to gather more in-depth information on airline customers and the causes of their complaints. Comparing future research outcomes to this study's findings would provide significant insights into customer complaints and sentiments across different social media platforms. It will help researchers detect similarities and differences in customer complaints and sentiments.

Furthermore, since some of the demographic characteristics of airline passengers were not available for the study, future researchers should analyze the social media profiles of airline customers to extract demographic information such as gender, age, educational background, income levels, and trip reasons. Examining these factors in connection to the frequency of complaints would provide insight into how they influence passenger complaints regarding service quality.

Lastly, future research on sentiment analysis for Brussels Airlines could explore alternative classification techniques or approaches, such as machine learning or deep learning methods. Classifiers like Naive Bayes or Support Vector Machines could be used to predict customer sentiment, and the results could be compared to the findings of this study, providing further insights and validation.

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APPENDIX 1. TABULAR RESULTS OF SENTIMENT ANALYSIS

Sentiment Polarity	Count of Polarity	Percentage of Sentiment Polarity
Negative	1493	66%
Neutral	181	8%
Positive	585	26%
Grand Total	**2259**	**100%**

Appendix 1. Results of Sentiment Analysis