Journal of Air Transport Management 103 (2022) 102232

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Identification of opinion trends using sentiment analysis of airlines passengers' reviews

Siavash Farzadnia *, Iman Raeesi Vanani

Department of Management and Accounting, Allameh Tabataba'i University of Tehran, Iran

ARTICLE INFO

Keywords:
Customer opinions
Management recommendations
Passenger satisfaction
Topic modeling
Sentiment analysis

ABSTRACT

Receiving customer opinions on products and services provided by companies is one of the main needs of company managers to improve products and services. Today, it is common to use social networks, messengers, and review websites to receive data from customer opinions. But analyzing the data received from these sources due to their huge volume requires an efficient tool. In this study, textual data obtained from the reviews of passengers of the top 10 airlines in the Middle East region have been analyzed and evaluated. First, we identified the main topics that are hidden in the customers' reviews by topic modeling method. In the next step, we evaluated the level of passenger satisfaction based on the topics identified in the modeling stage, by using sentiment analysis on passenger reviews to demonstrate the strengths and weaknesses of the airlines in providing various services to customers. In the end, management solutions and recommendations are provided to airline managers. The proposed method is a new approach for evaluating customer satisfaction and can be used as a guide for airlines to develop marketing strategies to attract new customers and increase their market share.

1. Introduction

Nowadays, many manufacturers, organizations, and service providers require customers' reviews and feedback to evaluate their products and service quality (Greer and Lei, 2012). In the past, there were different direct methods to learn about customers' opinions on products via interviews, questionnaires, surveys, text, phone, and email messages. However, these methods of communication have changed due to the recent advances in information technology and increased use of the internet and its availability to the public resulting in utilizing innovative and modern methods of communication with customers (Jin et al., 2016; Raeesi Vanani, 2017; Riaz et al., 2019). This has, in turn, enabling access to a new source of customer information that decreased the need to direct communication with the customers. For instance, social media, messengers, online groups, public and private channels as well as various websites can gather customer opinions on specific topics or industries. Thanks to the comprehensive information relevant to the topics on these websites, it becomes possible to suggest vast and broad data in areas such as marketing and customer service and customer relations and management to the audience (Park et al., 2019; Sohrabi et al., 2012). The data covers not only the general opinion on products but also the customer's specific comments and expectations.

The airline industry requires to continuously monitor and analyze the customer reviews on its service. In previous articles, researchers have explored various aspects of airline passenger services. Tsafarakis et al. (2018) used MUSA (Multicriteria Satisfaction Analysis Method) to measure passengers' satisfaction with several service features in Aegean Airlines and to identify the features that need further improvement. Unlike other methods, the MUSA method utilizes the qualitative form of satisfaction data and does not involve robust assumptions about the satisfaction or behavior of customers (Lachnidaki et al., 2021). The model system is based on a multicriteria analysis (aggregation-disaggregation method and linear survey-based software) which can deliver useful results by evaluating explicable indices of customer satisfaction. Passengers were invited to rate their experience with Aegean airlines via some surveys comprising a set of criteria. The results of this modeling research revealed that customers are dissatisfied with the ticket price and the extra charges. In some studies, even the gender factor has been studied, the impact of gender of passengers on the airline industry was studied by Kurtulmuşoğlu et al. (2018). The study addressed important service factors prioritized by female and male passengers by rating the airlines based on the proposed method in a linguistic framework. The review of airlines has been a controversial topic for the airline industry, and there is a need for robust data evaluation due to a variety of

* Corresponding author.
E-mail addresses: s_farzadnia@atu.ac.ir (S. Farzadnia), imanraeesi@atu.ac.ir (I. Raeesi Vanani).

https://doi.org/10.1016/j.jairtraman.2022.102232
Received 26 December 2021; Received in revised form 1 May 2022; Accepted 16 May 2022
Available online 27 May 2022
0969-6997/

passengers' expectations. As such, data analysts in this industry are greatly involved inefficient data gathering and assessment based on customer reviews.

On the other hand, with the evolution of artificial intelligence and related disciplines such as machine learning, the application of computer processing methods using mathematical algorithms has increased to understand the hidden patterns in data, which is known as data mining (Hanafizadeh and Paydar, 2013; Raeesi Vanani, 2019). Among the data that can be processed is textual data that can be used to identify hidden knowledge in texts using a variety of text processing methods. Hong and Park (2019) have used text mining of airline review data for evaluating marketing and corporate performance. They suggested a procedure that contains the process of extracting the most repetitive keywords by text mining methods and grouping them into different clusters. A combination of measurement and clustering techniques to analyze content related to the keyword extraction method, including text data from other scientific literature was utilized. The major finding of the research was believed to be the usefulness of keywords to show distinctive features. Moreover, the most repetitive keywords were found to be those extracted from text mining. Based on the results obtained, the author suggests that factors such as "recommendation" and "satisfaction" better be managed distinctively in the area of service management of the airline industry. Text mining and its related analyses such as sentiment analysis can help researchers working on opinion mining to understand the consumers' opinions on products and services more effectively and timely than before (Ravi and Ravi, 2015).

Furthermore, natural language processing is another discipline of artificial intelligence focusing on interactions between humans and computers via natural language. Majority of natural language processing methods that try to recover and understand the meaning of human languages are based on artificial learning techniques (Vanani and Majidian, 2020). However, the technique used in this study involves the initial identification of remarkable and important topics in the reviews of airlines' customers who recorded their comments on airlinequality.com using topic modeling. Topic modeling is a type of probably produced model which has recently been used in computer science mainly by utilizing text mining and recovering information (Sohrabi et al., 2018; Vayansky & Kumar, 2020). The topic modeling techniques are statistical analysis methods that analyze words in the text and find the topic of the text, they can also reveal the relations of different topics and how they change over time (Bastani et al., 2019; Cheng et al., 2014; Hu et al., 2014). These techniques do not need any preliminary assumptions about the topics or text labels and their inputs are main and raw text; they are classified as unsupervised algorithms (Korfiatis et al., 2019).

In this paper, firstly three standard topic modeling algorithms were compared to find the most appropriate topic modeling algorithm for all data of this research. Next, the winning algorithm was selected based on the determinant coherence score, which is defined as a factor to measure the efficiency and quality of topic modeling.

The modeling was carried out by finding prominent topics that were used as the input parameters of the model. The next step involved the identification of related words and labeling them as a topic for each group of words, which determines the titles of the prominent topics. After identifying the main topics found in the reviews using the above process, an assessment of the level of customers' satisfaction with the services provided by each airline was aimed. To achieve this, the polarity measurement process was used. In this process, the final results of negative and positive comments for each topic were calculated, and eventually, the final score which demonstrates the level of customer satisfaction about each topic was obtained. Considering the contents of this section, it is necessary to provide research questions to evaluate the efficacy of the proposed method. The research questions are as follows:

RQ1 What are the most prominent topics in the reviews of airline passengers?

RQ2 What is the result of analyzing passenger feedback on the topics identified in the reviews for airline managers?

To answer the questions of the article, there is a requirement for a specific procedure of data extraction and its preprocessing to select the optimal model with appropriate input parameters to identify prominent topics and then adopt a passenger feedback system for evaluating airline services to provide management solutions.

In conclusion, the purpose of this study can be summarized as follows: First of all, identifying the prominent topics that airline passengers pay attention to during their trip, as well as measuring the level of satisfaction with the services received. Secondly, the use of these results to compare the quality of services provided among selected airlines in the Middle East. Finally, the use of the results of this study to provide recommendations to managers of these companies to identify potential deficiencies and improve services to increase customer satisfaction.

The rest of the paper is organized as follows: Section 2 provides the background and a literature review as well as a theoretical foundation; Section 3 demonstrates the materials and methods; Section 4 describes the experiments, results, and evaluation; Section 5 contains the discussion and conclusion; and Section 6 concludes with future research directions.

2. Literature review

2.1. Survey of customer satisfaction in the airline industry

Airline companies are trying to use customer data in conjunction with data mining methods to create efficient decision-making systems for receiving competitive advantages. Achieving these systems in a highly productive manner may help to reduce operating costs, provide better customer service, competitive advantage, increase operating profit margins, and increase shareholder satisfaction. And this is not possible without customer satisfaction (Lacic et al., 2016). Jiang and Zhang (2016) had studied the quality of service in four main airlines in China's domestic market to find the relation between their service quality and customer satisfaction. Using a probit model to evaluate the factors influencing customer satisfaction and loyalty, their results showed that it is essential to distinguish between business and recreation travelers while studying the satisfaction level; for instance, ticket pricing had a positive impact on passengers' overall satisfaction and loyalty for leisure travels, but not on the satisfaction and loyalty of business passengers. Some factors such as gender, income, and education are demonstrated to be decisive for one group of passengers but not for another based on the probit model. The study, however, was not able to explain why some important variables did not recommend strategies for airlines to achieve a higher level of customer satisfaction and loyalty.

In another study, Choi (2017) had detailed the results of two kinds of bootstrap regression analysis to assess the effectiveness and efficacy changes of US airlines over 10 years. The finding of the study suggests that generally, each airline merger creates a different level of synergy, based on the airline's specific route and cost setting. Besides, strategic merger and acquisition (M&A) initiatives of airlines with different business models need to be considered to strengthen the system and cost synergy effects of post-M&A.

A comprehensive feature study using the Skytrax air travel review portal was conducted by Lacic et al. (2016). Ratings and recorded features from airport, lounge, and seat reviews were used to explain which factors impact traveler satisfaction. They created a classification program for predicting passenger satisfaction based on the best-performing rating features. The results revealed that travelers' satisfaction can be anticipated with high accuracy as a meaningful correlation between review text sentiment and final traveler satisfaction. In an attempt to conduct a productive model to measure the most important attributes of each airline for attracting and satisfying travelers, Medina-Muñoz et al. (2018) examined the air passengers at one of the major airports in Spain.

Based on their discoveries, the four most important factors for passengers were safety and reliability, price of tickets, and response to requests. Moreover, they suggested that air travel frequency as an air travel behavior as well as other characteristics (location, age, gender, marital status, education level, work status, and income level) influenced passengers' preferences in areas such as price, flight route and connections, safety and reliability, and cabin space. Some of these findings are in agreement with previous works (Chen and Chao, 2015; Dolnicar et al., 2011; Teichert et al., 2008). The study findings also provide suggestions at a professional level to improve the attractiveness of airlines as the categories of important attributes are competitive methods that can be considered by airlines to better design their business strategies.

2.2. Topic modeling

One of the unsupervised methods in machine learning is the topic modeling technique, which is used to summarize texts to identify the topics mentioned throughout the text (L. Hong and Davison, 2010). The topic modeling techniques enable us to find hidden topics in text documents and act as a powerful text-mining tool for the classification of documents based on topic extracted results (Arun et al., 2010). This technique is considered as a method that is part of the category of soft clustering. Documents (in this study, customer reviews) are a combination of different topics that refer to them with different degrees of membership, which are also being used as a text-mining tool to sort documents on the inferred results of the subject (Arora et al., 2013). It is a kind of possible production model that has been used in recent years in the area of computer science with a special focus on text mining and information retrieval.

Among topic modeling algorithms, we can mention latent semantic indexing (LSI), nonnegative matrix factorization (NMF), and latent Dirichlet allocation (LDA). Experimental evaluation of both LDA and LSI was carried out to obtain responses in terms of efficiency and effectiveness. LSI was found to be superior to LDA. LSI has been revealed to be better than LDA in supporting the suggestion of similar plots, although it does not appear to be significantly beneficial for the commercial approach (Bergamaschi and Po, 2014). NMF is a member of the family of linear algebra algorithms and is known as the factor analysis method. It is an unsupervised technique that uses a matrix factorization approach (Kuang et al., 2015). One of the differences between NMF and LDA is NMF corrects values for the probability vectors of the multinomials, however, LDA allows the topics and words to be varying themselves.

2.3. Sentiment analysis

The purpose of sentiment analysis is to determine the consumer's attitude toward a particular topic or product. Therefore, different platforms can be used to achieve positive, negative, and neutral attitudes. These platforms are generally categorized as automatic or manual processing, many businesses use a hybrid model. We have an overview of related research in this area.

In order to ensure the efficiency of their companies, managers and marketers can utilize systematic benchmarking through sentiment analyses. By analyzing customer sentiment, airline managers are able to compare the practices of their peers and adopt these practices in their own companies to improve future efficiency. Moreover, airline managers can use sentiment analysis results to support other objectives, including allocating financial resources and identifying inspection priorities (Mostafa, 2013). The customers' review on various Italian and Spanish monument reviews on TripAdvisor was analyzed based on the Sentiment Analysis Method (SAM) by Valdivia et al. (2019). They had detected some discrepancies between the "user polarity" and automatically extracted polarities detected by sentiment analysis, for instance, it appears that users rate their visits positively, but sometimes negative wording and ratings are detected. Utilizing a polarity aggregation model which is obtained by the geometric mean function of the polarity of the user and a SAM, they were able to match the user polarity and the sentiment extracted by a pre-trained method SAM. The polarity aggregation model attained more reliable scores using information obtained from two sources: users and the algorithms for automated detection of sentiments. In a study on assessing the level of customer satisfaction using sentiment analysis of websites, Gitto and Mancuso (2017) have explored the data extracted from blogs and by using text extracting programs to assess the level of service by airport customers. The findings demonstrated that passengers focus their valuations on food and beverage services and shopping zones. It also showed that airport managers can use blogs to understand the needs and satisfaction of their customers.

2.4. Hybrid approaches in evaluating customer satisfaction

Much of the research that has been done on customer satisfaction with airline services presupposes pre-defined services and evaluates customer feedback based on these topics, while the weight and impact of these topics and the frequency of comments about the subject matter have been different. Various methods have been used to combine the two methods of topic modeling and sentiment analysis in the past. Here are the findings of some of the studies.

Adeborna and Siau (2014) used a new approach for Sentiment Topic Recognition (STR) modeling based on Correlated Topics Models (CTM) to concurrently capture user's opinions and topics intrinsic to such opinions by extracting the underlying topics which help with providing general knowledge and scope of the different consumer feelings. Besides, it tries to answer questions about the motives of each category of sentiment in a dataset and effectively examines the total scope of the sentiment. They obtained promising results using their method on a limited number of tweets on three airlines. There are, however, some limitations to this lexicon-based tactic used in sentiment detection, for instance, it is inadequate in detecting figurative expression. In the study conducted by Lim and Lee (2020), they first identified the topics using topic modeling with the LDA method and divided these topics into 5 categories named tangibles, reliability, empathy, responsiveness, and assurance then analyzed the passenger's sentiment on these 5 categories. Finally, they have been able to measure the importance and satisfaction of passengers with this method. Recent research was conducted using some kind of opportunity algorithms based on topic modeling and sentiment analysis on social networks. Initially, each topic was defined from the customer perspective by the LDA using social network data. Then, the degree of prominence and satisfaction of each topic was calculated. The importance of the topic is calculated on the participation of the share, while the level of satisfaction with the topic is calculated based on the participation of emotions. Finally, using the opportunity algorithm, the value of the opportunity and the improvement of product-related issues are determined from the customer's perspective (Jeong et al., 2019).

After reviewing the past literature on customer feedback processing, each of the methods used has been able to reveal some aspects of hidden information in the texts. However, there was a need for a comprehensive application that encompasses all the steps in order to provide analysts with a framework through which they could process the opinions of customers of service-oriented companies, particularly airline companies. Our purpose was to develop a multi-step methodology for designing a comprehensive application from the stage of data collection and preprocessing up to the stage of modeling and visualization. Previous research discussed in this section used a specific algorithm for text analysis and topic modeling, while our proposed method searches for a suitable algorithm to process textual data. By using the coherence criterion, we created a competition among the three topic modeling algorithms (LSI, LDA, and NMF) to select the optimal algorithm for modeling. The significance of this method is to identify clusters with more frequency and distinction from each other, to better understand the content of each topic by identifying keywords that are closely related within each cluster. The proposed method is a new approach for processing the opinions of customers of the airline industry and is referred to as the contribution of our study to the modeling stage. Furthermore, in the sentiment analysis stage, by creating a data dictionary, the average polarity score has been calculated for each topic and each airline. This method has never been applied to a similar study in the field of analyzing airline customers' opinions, therefore, the findings can provide new insights into airline industry analysts. Overall, the methodology of the study, which integrates topic modeling and sentiment analysis provides a new approach for evaluating passenger satisfaction with the services provided by airlines for analysts and managers. The stages of this methodology are presented in detail in Section 3.

3. Materials and methods

3.1. Data preprocessing

Dataset: The data in this paper is collected from the reviews of airlinequality.com website users from June 2015 to May 2019 for the top ten airlines in the Middle East. This data includes the texts obtained from the reviews of the airline customers and the numerical data equivalent to the points that the customers have for the various services provided by the airline companies, which users can submit reviews through the review system of this website as shown in Fig. 1.

According to the information in Fig. 2, the number of reviews registered in the specified period was 4933 reviews, which is limited to 4932 due to the duplication of one of the reviews. Of this number, 24% of the reviews are assigned to the passengers of Emirates Airlines, and it has the highest frequency among the airlines studied in this research and Turkish Airlines with 21%, Qatar Airways with 21%, Etihad Airways with 17%, Oman Air with 4%, Flydubai with 3%, Kuwait Airways with 3%, Saudia with 3%, Royal Jordanian Airlines with 2% and Gulf Air with 2% are next.

Filtering and cleaning data: The collected data includes a combination of textual and numerical data and scoring stars that users have recorded on this website using the review system shown schematically in Fig. 1. In this study, only textual data are considered that are separated from other data to prepare for the cleaning data step. After separating textual data, we should clean them. Cleaning is the process of standardizing and removing irrelevant characters and texts. This step consists of a total of 9 processes to prepare the text for modeling operations. These 9 steps are as follows:

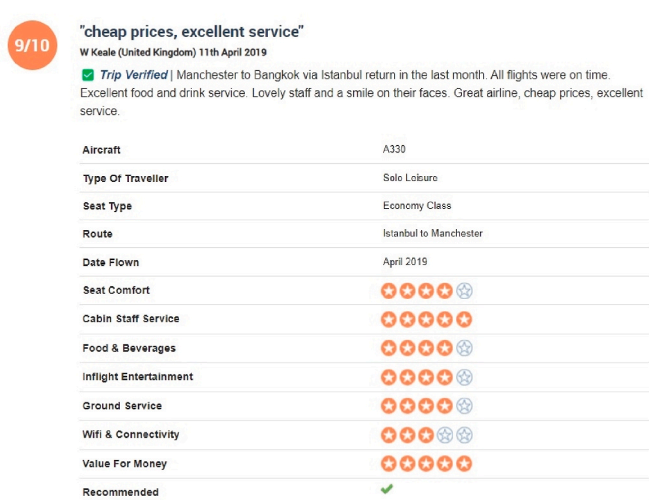


Fig. 1. Passenger reviews about airline services.

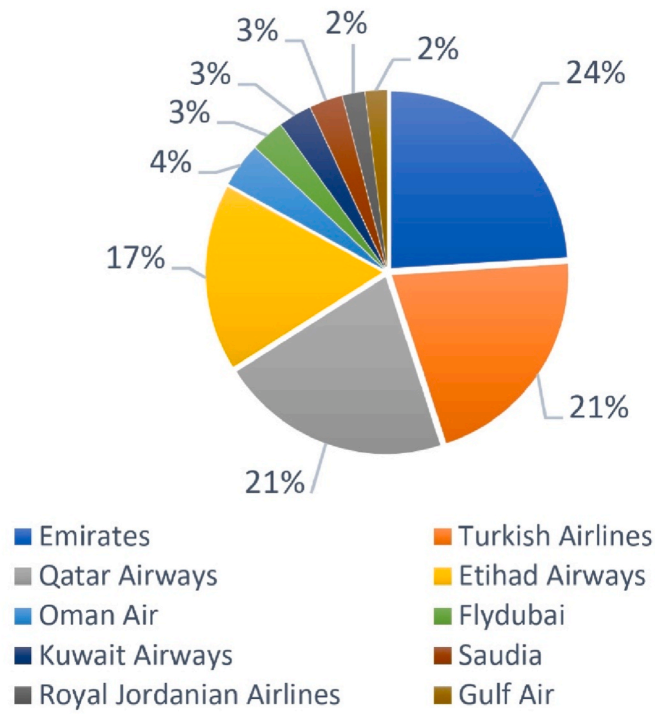


Fig. 2. The percentages of number of reviews per airline.

I ***Normalizing words***: Unifying text data, although often overlooked, is one of the simplest and most effective forms of text preprocessing. This step is used for most problems related to text extraction and natural language processing and will significantly contribute to the expected output quality.

II ***Removing punctuations***: Clear a set of symbols such as [! ”# $% &’ () * +, -./: ≤>? @ [\] ^ _ ’{|} ~].

III ***Deleting blank space***: The existence of space and space between words increases memory occupation and slows down the modeling process. As a result, these spaces need to be removed.

IV ***Tokenization***: tokenization is the process by which a given textual data is subdivided into smaller language elements called tokens. Words, numbers, punctuation, and other items are among the language elements known as tokens.

V ***Removing numbers***: Depending on the type of problem defined, sometimes we do not need the numbers mentioned in the text, therefore we also remove such elements from the text. Usually, the “regular expression” method is used to remove numbers from textual data.

VI ***Removing sparse words***: Sometimes it is necessary to remove sparse words from textual data. These words include the names of people, countries, cities, names of airports, etc.

VII ***Removing stop words***: Stop words are the most common words used in a language; for instance, words like “the”, “on”, “is”, “all”, and “a” are ineffective words in English. Because these words do not have a specific semantic load and do not convey significant semantic content, they are usually removed from textual data. Programmers and application developers can remove ineffective words from textual data by creating dictionaries or using pre-prepared dictionaries.

VIII ***Expanding abbreviations***: Some words and expressions in extracted texts have an abbreviated form. To coherence and unify such expressions, we must convert these abbreviations to their full names.

IX ***Finding the roots of words***: Generally, in different texts, some words are close to each other but are written in two or more different forms. The rooting operation makes it possible to convert different forms of a word into a single form. This reduces the number of attributes and removes different shapes of a word, and the computer can consider different shapes of a word as one.

The process of cleaning the text is described in Fig. 3 step by step with an example. Noting that some of these steps can be changed priority.

Bag of words: It is a simple display employed in the processing of natural language and data retrieval. Also known as the vector space model. In this model, a text like a sentence or a document is displayed as a package of several sets of words, regardless of grammar or even word order. The word package converts text into a word occurrence matrix within a document to be used as input in the modeling phase.

3.2. Modeling

Model selection: In this step, to perform topic modeling on the data set, we seek to select the best algorithm. Our criterion for selecting the best algorithm is the use of a coherence value score. Therefore, there is a competition between the selected algorithms to select the optimal algorithm for the next step. For a better understanding of the algorithms presented in this section, we will briefly review and describe the theoretical foundation for each of the LDA, LSI, and NMF algorithms.

- ***Latent Dirichlet allocation -*** LDA in natural language processing allows for the analysis of sets of observations in terms of unobserved groups that explain why some parts of the data are similar (Gross and Murthy, 2014). This method was created to model several hidden variables in a set of texts that contain words. In fact, in a text containing many words, each word can be assigned some titles with a certain probability, which eventually combines to form a text and its topic. (Blei et al., 2003).
- ***Latent semantic indexing -*** LSI or Latent Semantic Analysis (LSA) (both of them use the same technique) is an information retrieval system by indexing terms and detection method that uses some mathematical techniques such as singular value decomposition to recognize patterns in the relevance between the phrases and concepts contained in an unstructured text (Foltz et al., 2000). LSI is a method using Singular value decomposition (SVD) to form semantic generalizations from the textual section. LSI involves representing a text as a matrix, where each row represents a unique word and each column represents a part of the text. Each cell contains the frequency of word occurrence. Each cell represents the frequency of the word occurring in the text. The frequency of each cell is weighted by the function. Word importance indicates how important a word is within a certain context and how much information the word carries in general.

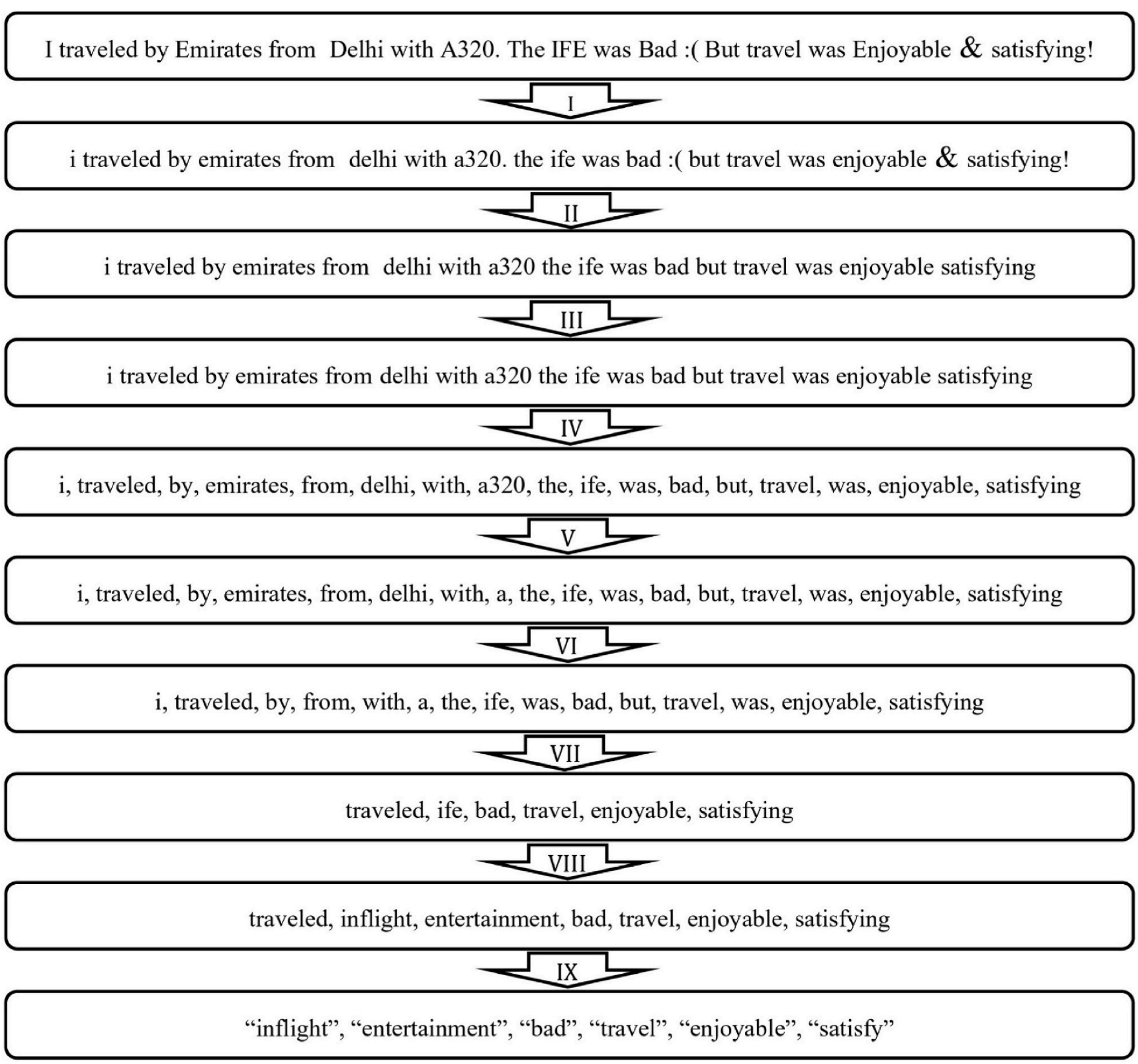


Fig. 3. Example of text preprocessing steps.

- ***Nonnegative matrix factorization -*** NMF estimates a nonnegative matrix by the product of two different low-rank nonnegative matrices. Furthermore, NMF provides a semantically meaningful result that is easily interpretable in clustering applications; it has been commonly used as a clustering method, particularly for text data, and as a topic modeling technique (Kuang et al., 2015).

Model execution and aspect extraction: In this step, the model that won the competition between the algorithms in the previous step is executed on the data, but before implementing the model, we require to specify the value of the input parameters. To achieve this, we evaluate the model with different parameters in order to select the most appropriate parameters to ensure the model output is optimal. We also need an index to confirm the results of modeling algorithms. For this purpose, we use the coherence score.

- ***Coherence score***- As an evaluation criterion, identifies a single topic by calculating the degree of semantic similarity between words that have a high score on a topic. It also helps us to measure the distinction between topics that are semantically interpretable in statistical inference (Stevens et al., 2012; Suaysom and Gu, 2018).

After implementing the model and identifying the main topics from the words with the highest frequency, the most relevant words are identified to be used in the next step in calculating the polarity. The selection of related words and phrases from among 40 words is most frequent.

3.3. Sentiment detection

Polarity calculation and sentiment analysis: We require this operation to determine the average polarity of airline passengers' reviews, which indicates their level of satisfaction or dissatisfaction with the services provided in each identified topic. This opinion can be positive or negative or neither of them and can be classified as a neutral opinion. The input of this step is the dictionary of the words selected in the previous step, as well as the special preprocessing suitable for this operation in the data cleaning step. The calculations obtained from this section enter the process of sentiment analysis. It is a study that tries to express the feelings, behaviors, opinions, and analysis of different people concerning their entities and characteristics. The output of the operation of the previous step is calculated for each identified topic per airline and is prepared in tabular form by displaying the heat map for a better comparison between the services of different airlines.

3.4. Interpreting

Visualization and reporting: visualization is one of the best ways to express and present the results and analysis of data mining. Using data visualization methods, in addition to presenting the results obtained, knowledge of graphs and diagrams can also be explored. The information obtained from the heat map in the previous step can be displayed in the form of various comparative diagrams using the visualization tool in order to better interpret the results. In order to provide management advice, we interpret and report the information obtained from the graphs and tables obtained from the previous steps. The information obtained from this step is provided to managers to improve and reconsider the provision of services and decisions, as well as travelers who have planned for their next trip. A visual representation of the four key stages of research methodology that are discussed in detail in this section is shown in Fig. 4.

4. Experiments and evaluation

4.1. Topic modeling implementations

After completing the preprocessing of the texts, we entered the modeling stage to identify and run an algorithm on the research data. First, the bag of words matrix is created as the input to the modeling algorithm. At this stage, we need to select the appropriate algorithm to continue working and also require to determine the optimal value of input parameters to implement topic modeling algorithms. One of the main parameters of our input, which is important to answer one of the article questions, is the number of topics that are identified from the text of customer reviews. In order to find the optimal number between 3 topic modeling algorithms; LDA, LSI, and NMF in the range of 6–20 topics, the value of the coherence is calculated to identify the selected algorithm. After execution, the results are displayed in Fig. 5.

Based on the information in Fig. 5, the values obtained from the implementation of the algorithms indicate that the number of topics 7 to 11 is the number of prominent topics that can be candidates for the selected algorithm input. The LSI algorithm with a coherence score of 0.447 in 8 topics has the highest score in the range of 6–20 topics. Also, the NMF algorithm with a score of 0.427 in 11 topics is in the optimal

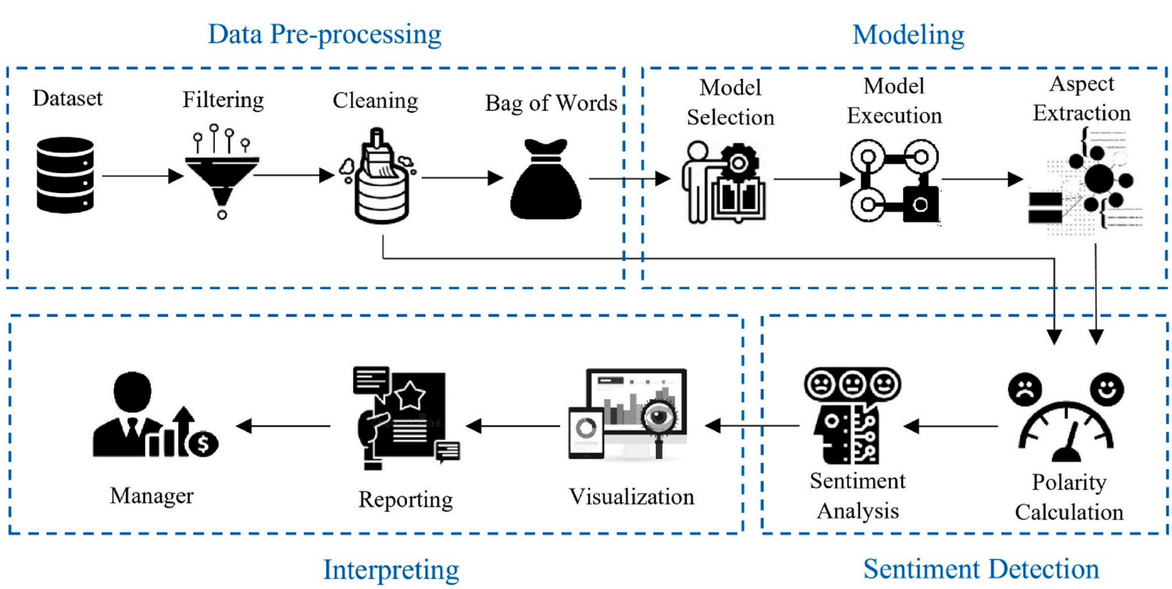
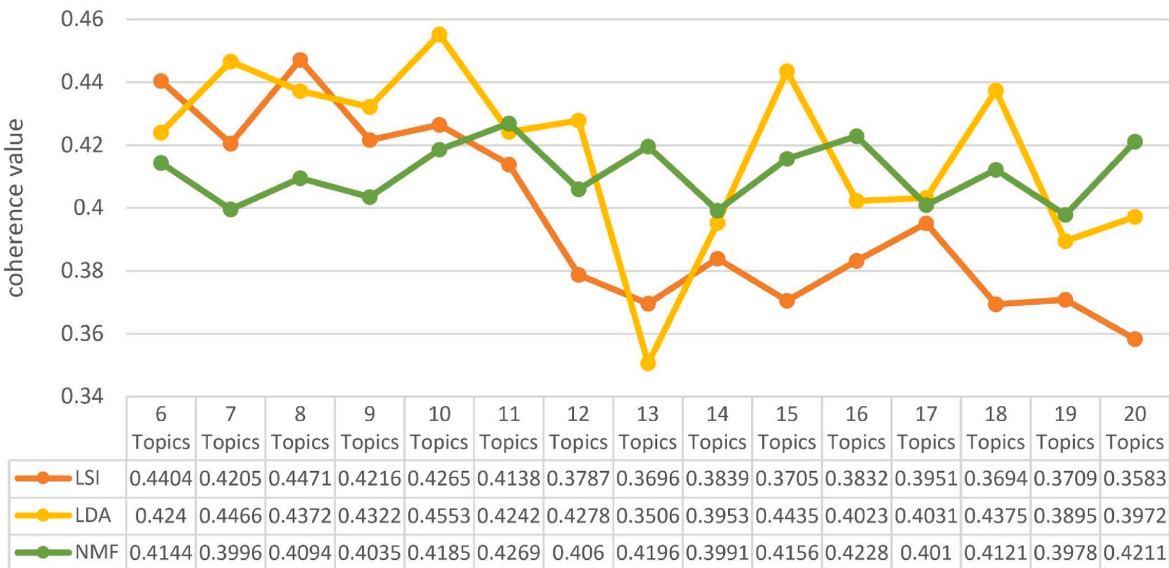


Fig. 4. Methodology of research.



	6 Topics	7 Topics	8 Topics	9 Topics	10 Topics	11 Topics	12 Topics	13 Topics	14 Topics	15 Topics	16 Topics	17 Topics	18 Topics	19 Topics	20 Topics
LSI	0.4404	0.4205	0.4471	0.4216	0.4265	0.4138	0.3787	0.3696	0.3839	0.3705	0.3832	0.3951	0.3694	0.3709	0.3583
LDA	0.424	0.4466	0.4372	0.4322	0.4553	0.4242	0.4278	0.3506	0.3953	0.4435	0.4023	0.4031	0.4375	0.3895	0.3972
NMF	0.4144	0.3996	0.4094	0.4035	0.4185	0.4269	0.406	0.4196	0.3991	0.4156	0.4228	0.401	0.4121	0.3978	0.4211

Fig. 5. Coherence value calculation according to the number of topics.

state. Finally, the LDA algorithm with a score of 0.455 in 10 topics has the highest score in the range of 6–11 and is also compared to the scores calculated in LSI and NMF algorithms. A higher coherence score has the advantage that the words in each category of identified clusters have a higher semantic similarity. Therefore, the clustering of topics is done with better quality, and labeling for each topic and distinguishing it from other identified topics is done to continue the steps more easily. As a result, in this article, the LDA algorithm is used to identify 10 hidden topics in the review text.

After determining the optimal number of topics in this step, we will implement the LDA algorithm for thematic structure. This technique is performed using the machine learning method without supervision, which results in the creation of thematic clustering. Therefore, we want to identify 10 distinct clusters of words, each of which represents a separate concept. Learning according to the input parameters is done in 400 iterations and the results are found in Fig. 6.

The most frequent topic among airline passengers' reviews has been the topic of "time" and time-related concepts. To achieve this title, the most frequently used words that have been identified in this cluster of words and have time-related concepts have been used. The presence of words such as "wait", "delay", and "time" indicates the concerns of passengers with the subject of "time". 21.8% of all comments are dedicated to this topic, which means the importance of time for passengers.

The second most recurring topic among passengers in the top 10 airlines in the Middle East is "cabin services". This shows the importance of passengers to the services they provide in their cabin on the plane. In terms of frequency, this topic accounts for 16.6% of the total comments. Passengers, regardless of the flight class for which they purchased the ticket and the price they paid, ask the airline for expectations such as quality of meals, efficient entertainment systems, proper cabin, and air

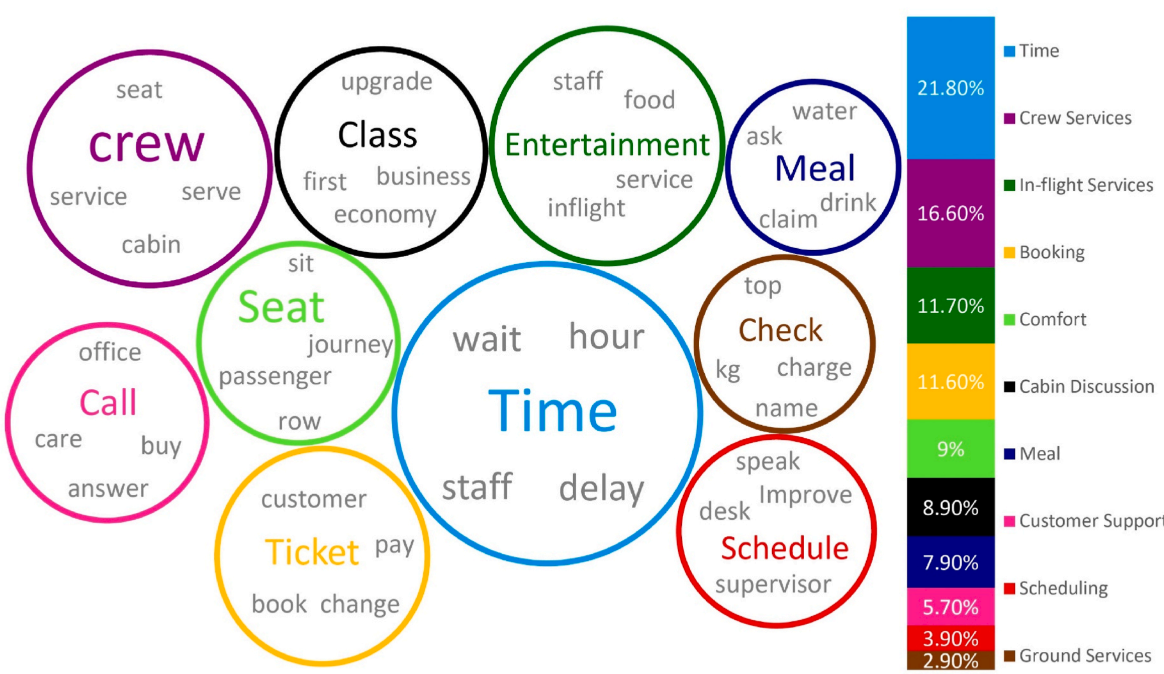


Fig. 6. Distribution of related topics and keywords in reviews.

conditioning.

The third prominent topic in the passengers' reviews is the requests related to the services of flight attendants. It has been criticized by many travelers and it contains 11.7% of all reviews.

The next topic that appears as the fourth topic in passengers 'comments is discussions about booking flight tickets and answering passengers' questions before and after the purchase of a flight ticket. The importance of this topic can be examined because travelers expect a reservation system that is user-friendly and efficient and provide them with suitable offers for booking the day and time of flight at a suitable speed, with low complexity and high execution speed. This topic dedicated 11.6% of all reviews to itself.

The topic of the comfort and convenience of the seat and the position that the passenger is in air travel has always been one of the important issues that passengers of different flight classes pay attention to. For example, many economy class passengers have often criticized the fact that they feel backache and back pain during the trip, so we named "comfort" as topic number five for better understanding. Keywords of this topic in other clusters also play a significant role due to the sharing of the word "seat". 9% of the comments directly mentioned this topic.

The sixth topic is the comparisons of the comments about the services provided in different flight classes and its details are mentioned. Passengers have reasonable expectations for the price paid for a plane ticket, and this is discussed in these perspectives. This topic is identified separately due to the fact that airline passengers, based on their previous experiences in air travel, make comparisons between the services of different flight classes on different airlines. Hence, in their critiques, they sometimes try to explain this topic in detail. 8.9% of the reviews are directly related to providing information about different flight classes.

The seventh topic refers to the nutrition of passengers and focuses on the quality of meals served to passengers during the flight. This is common to many comments in the form of this cluster of words and the second cluster that refers to the cabin features. It dedicated 7.9% of all reviews to itself.

The eighth topic refers to airline support services to its customers. Communicating with the customer and meeting the needs and questions they have about their flight builds more trust and satisfaction with the service of the airline. As a result, the lack of attention of some companies leads to criticisms that are sometimes seen in the comments. This topic got 5.7% of passengers in its cluster.

The ninth topic discusses the schedules and the process of accepting passengers from the waiting room to board the plane according to the plans made, therefore the procedure related to this process has been considered by passengers. 3% of comments directly mention this topic.

Finally, the tenth topic that has less repetition in the comments is the discussions about ground services, checking luggage, and guiding passengers at the airport. This is a common theme that passengers expect from airports and airlines, and is not limited to airline services. Just 2.9% of all passengers discuss this concept.

Tagging for each topic is done according to the keywords that have the most frequency. Of course, due to the existence of common keywords among the topics, they sometimes contain common concepts. However, to differentiate from each other and use them in the analysis of emotions, we have tried to be as recognizable as possible. Topics with 5 repetitive words in each topic that have been identified using topic modeling, along with topic labels and frequency of each topic are presented in Fig. 6.

Each traveler's opinion covers several topics. Sometimes each person's opinion can include all 10 identified topics. Therefore, the opinion of each passenger can be attributed to a different percentage belonging to each topic.

The series of related words are collected in the form of a dictionary for each topic in Table 1. To calculate the average score, the sum of the scores of the two words before and after them is calculated, and the average score will be the final score of each word dictionary. Words that are directly related to each topic are selected from among 30 repetitive words in each cluster of words to help the sentiment analysis model be more accurate.

Table 1
Topic-words dictionary.

Topic	Words Dictionary
Time	time, late, delay, minute, wait, hour, on time, …
Crew services	crew, staff, service, order, offer, claim, ask, attendant, …
In-flight services	snack, movie, screen, tv, wi-fi, internet, display, …
Booking	available, ticket, buy, sell, pay, cancel, online, website, …
Scheduling	schedule, control, voucher, announce, assign, …
Cabin discussion	cost, value, price, quality, business, upgrade, economy, …
Comfort	seat, leg_room, move, sit, row, aisle, leg, lounge, …
Customer support	board, refund, answer, information, customer_service, …
Meal	meal, dinner, breakfast, chicken, sandwich, menu, …
Ground Services	gate, visa, passport, security_check, duty_free, bag, …

4.2. Sentiment detection results

After identifying the hidden topics in the reviews and labeling the title for each topic, as well as analyzing the overall customer feedback for each airline, in this section, the average scores are calculated based on the scores obtained from the polarity analysis for each airline and topic.

Based on the polarity analysis performed on selected airlines in Fig. 7, we see a different frequency of positive and negative reviews than the total number of registered. In Qatar Airways, the ratio of positive to negative reviews about the quality of the company's services indicates the high satisfaction of the company's customers. It is followed by Emirates, Oman Air, Gulf Air, and Saudia, which have a good ratio. In contrast, Fly Dubai Airlines received a higher ratio of negative to positive reviews from customers, which indicates passenger dissatisfaction with the company's services. After that, Etihad, Kuwait Airways, Royal Jordanian Airlines, and Turkish Airlines are in the next ranks of the most dissatisfied passengers.

To analyze the feelings of passengers' feedback towards the services provided by the airlines, it is necessary to measure the degree of positive or negative expression according to its linguistic meaning and concept. Polarity score means the calculated average of positive or negative words and phrases in all reviews. Words like "great", "good", "well", and "superb" have positive scores that are included in the process, while negative words like "bad", "worst", and "terrible" are words with a negative polarity that have more negative weight. After a complete review of each comment, the overall score in the range of -1 to $+1$ is calculated for each comment, and after grouping according to the specified range, they get one of the positive, negative, or neutral labels. The results of combining the extracted topics through topic modeling and sentiment analysis model in the form of a matrix that shows the intensity and weakness of positive or negative reviews in the form of a heat map in Fig. 8.

The numbers are shown in Fig. 8 cells are the average scores given to services through polarity analysis, which can be considered as a measure of customer satisfaction. To note, by comparing the rows and columns of this matrix and considering the values of cells and their color intensity, darker dots indicate higher customer satisfaction with the services provided. The brighter spots indicate lower satisfaction or customer dissatisfaction. It is fair to say this matrix has quite a few applications: it can be used to compare various airlines in terms of identified topics, indicating a type of airline service in a specific field. It also can be used as a scale to measure the level of passenger feedback relative to competing companies. Most importantly, it is useful for each airline to compare the topics of interest and the relative satisfaction across different types of services provided to their customers. For example, we examined the results of sentiment analysis of Oman Airlines passengers in this matrix. Passengers' comments on booking and in-flight services are positive while on the topic of "time", the average score calculated is

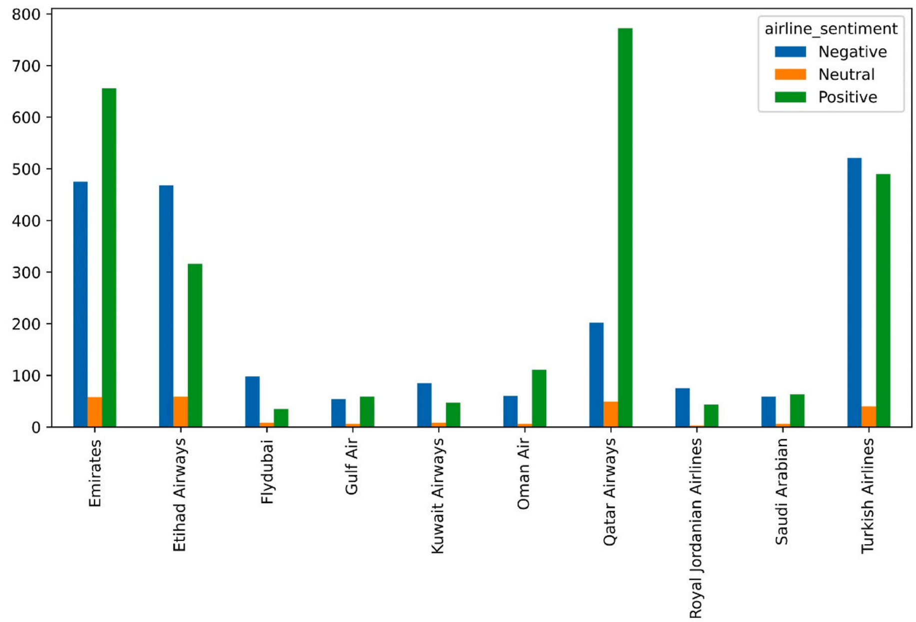


Fig. 7. Frequency of positive, negative, neutral reviews on airlines.

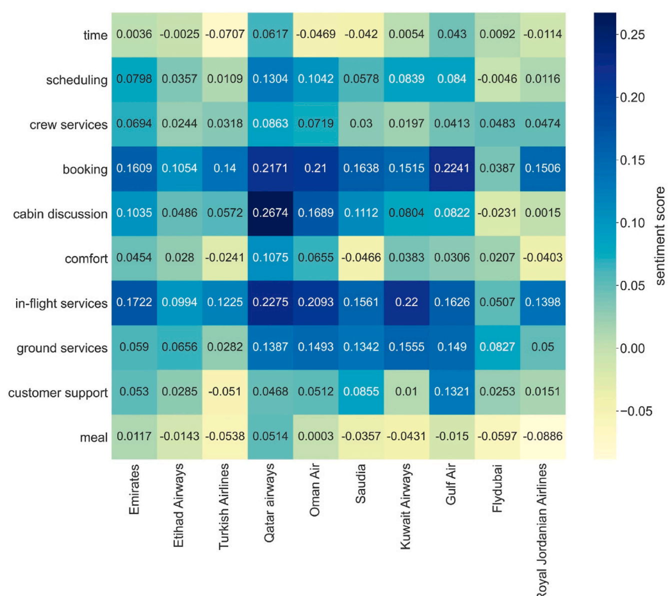


Fig. 8. Airline's sentiment analysis heat map based on related topics.

negative. Concerning the "food" topic, the sentiment score indicates a number close to zero, which shows moderate satisfaction with the quality of nutrition-related services provided during the flight. In the same way, related analyzes can be provided for different airlines.

4.3. Interpretation of the findings

For a better comparison between airlines in each topic, the information visualizes for better understanding in Fig. 9. The numbers shown are based on the matrix information in Fig. 8. In this chart, the level of passenger satisfaction with the services provided by the airlines, which is identified in the form of 10 topics, can be compared with companies in the same category. With the information shown in this chart, we can understand the shortcomings and weaknesses that have caused passengers' dissatisfaction with the services provided by competitors, and by rooting out these problems, we can try to eliminate or improve them. The items that are most visible in this diagram are indentations and protrusions that indicate a great weakness or strength in the services provided.

A different visual representation of the sentiment analysis results on the identified topics is shown in Table 2. The results are depicted in four categories: poor, medium, good, and excellent as shown as bolts. Based on the topics: "time", "comfort", and "meal", it is apparent that passengers are not satisfied with airline services. However, companies such as Qatar Airways and Emirates were able to receive moderate or good scores on these topics. Topics such as "ground services" and "crew services", "booking" and "in-flight services" are topics that are not in the weak category in any of the airlines due to the specified range. These findings indicate that the selected airlines provided satisfactory services on these topics. To provide appropriate solutions to provide to the management for each airline based on interpretation in Table 2, suggestions are given in Table 3.

5. Discussion and conclusion

In this article, we attempted to develop a procedure to be able to first identify the hidden topics in customer reviews on airlines' quality and secondly evaluate customer feedback on the topics found. This process includes several stages from the preprocessing phase to modeling and analysis of passengers' feelings and opinions, and finally the interpretation and analysis of outputs and reporting to be presented to the managers of airlines.

To identify the prominent hidden topics of airline passengers, we looked for a suitable method to show the convergence of passengers' opinions for better understanding customer needs and expectations. Among the common methods, there is a technique called topic modeling in which running the various algorithms such as LDA, NMF, and LSI on the article dataset could help us overcome this challenge. For this purpose, we first calculated the coherence value score for each algorithm for different values that indicate the number of topics to be identified to determine the optimal algorithm. After this stage and the selection of the winning LDA algorithm with a coherence value equal to 0.455, the modeling work was carried out on passengers' opinions. The 10 topics in various fields of airline services ranging from the arrival of passengers in the waiting hall and airport inspection to the services provided during

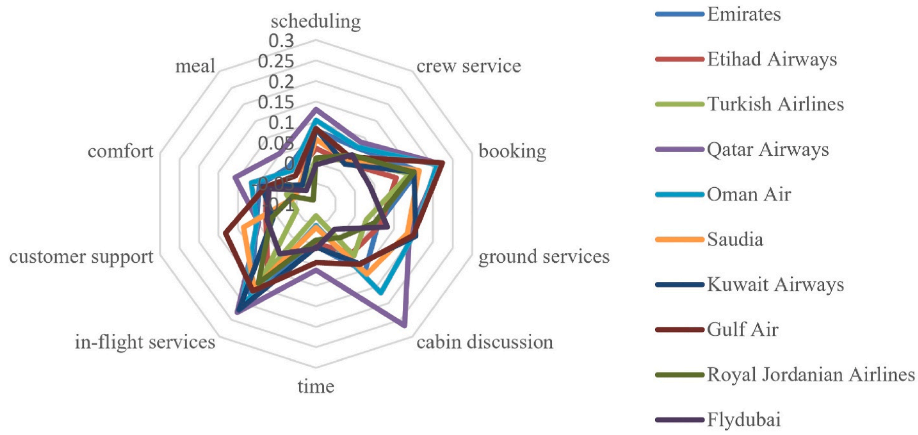


Fig. 9. Comparison of airlines average polarity scores on identified topics.

Table 2
Level of passenger satisfaction for the services of each airline.

	Emirates	Turkish Airlines	Qatar	Oman Air	Etihad Airways	Saudia	Royal Jordanian	Kuwait	flydubai	Gulf Air
Time	●●	●	●●	●	●	●	●	●●	●●	●●
Crew services	●●	●●	●●	●●	●●	●●	●●	●●	●●	●●
In-flight services	●●●	●●●	●●●●	●●●●	●●●	●●●	●●●	●●●●	●●	●●●
Booking	●●●	●●●	●●●●	●●●●	●●●	●●●	●●●	●●●	●●	●●●●
Scheduling	●●	●●	●●●	●●●	●●	●●	●●	●●	●	●●
Cabin discussion	●●●	●●	●●●●	●●●	●●	●●●	●●	●●	●	●●
Comfort	●●	●	●●●	●●	●●	●	●	●●	●●	●●
Customer support	●●	●	●●	●●	●●	●●	●●	●●	●●	●●●
Meal	●●	●	●●	●●	●	●	●	●	●	●
Ground Services	●●	●●	●●●	●●	●●	●●●	●●	●●●	●●	●●●

air travel as well as the delivery of luggage to passengers were identified.

Furthermore, to address the second question of the research, the analysis of the reviews of passengers and the outcome of positive and negative opinions using polarity analysis, as one of the methods to explore the sentiment of travelers to prepare reports, was performed. The results of the sentiment analysis stage are shown numerically in Fig. 9, Using the proposed method has enabled us to convert the data in clusters of words, phrases, and sentences from qualitative to quantitative information, and to have a better insight into the quality of service provided by airlines using visualization tools. Finally, this achievement has led us to use this information to suggest recommendations for the management of each company regarding the services provided, which are summarized in Table 3.

In the proposed approach to optimizing the results of the topic modeling stage, a process of competition between the algorithms proposed in the modeling section has been performed. The reason for this is the different performance of topic modeling algorithms in different datasets (Sun et al., 2009). By doing this step, we were able to select the best algorithm for data analysis. The result of this process has been the identification of clusters of topics with keywords that are close to each other in terms of content and different from other clusters. Besides, Comparing the results of current research with previous research which has used topic modeling algorithms on airline passenger reviews (Korfiatis et al., 2019; Lim and Lee, 2020) shows similarities e.g. in terms of the topics identified upon performing the modeling process in the first section and identifying 10 repetitive topics in the comments. However, our results show that one of the prominent clusters found here is the topic of customer support, which is the 8th most recurring topic in customer feedback, this is one of the achievements of this research and refers to the importance of customer support services that can distinguish between different airlines and encourage customers to receive services from a particular airline.

Moreover, we used a new method to combine topic modeling with sentiment analysis by creating a word dictionary for each topic and calculating the total weight of the effective words in the overall score for display and reporting to interpret information. Unlike the sentiment analysis stage performed by Riaz et al. (2019) using the polarity analyses in which a three-phase classification (negative, positive, and neutral) was used to show the level of customer satisfaction that we used in current research (as shown in Fig. 8), this approach provides more details of the information encompass in our customer opinions and give better insight for future improvement in quality of delivering service to customers.

In summary, due to the competitive nature of airlines' function and their service offerings, the results of this research can be used as a guide for airlines that are concerned about maintaining their competitive edge and developing marketing strategies that attract new customers and increase their market share. The findings of this study also provide professional implications and suggestions for evaluating customer satisfaction by analyzing customer opinions on online platforms. The contribution of this research relates to the development of a new approach to identify the strengths and weaknesses of airlines in the form of identified topics and has led to the emergence of results that can provide solutions and recommendations for managers to eliminate disadvantages and improve customer experience.

Table 3
Airlines management recommendations.

Airline	Recommendations
Qatar Airways	There is a good satisfaction level with Qatar Airways' services in the reviews of passengers, however, there is still room for improvement in terms of passenger nutrition and time issues, and customer support services.
Emirates	The level of passenger satisfaction with the service is often average and good. But weaknesses in "customer support", "time" topics and delays in providing services, and criticisms about the quality of nutrition have been seen that require to be improved.
Etihad Airways	The main weaknesses of this airline can be attributed to its time delays and the quality of food served to passengers, along with reports of poor service and poor stewardship communication with passengers. It is recommended to take decisions to reduce the time of procedures such as check-in before the flight.
Turkish Airlines	It scores low on "comfort", "customer support", "time" and "meal" topics and delays, and on-the-fly nutrition, indicating passenger dissatisfaction, therefore the company needs to redouble its efforts to improve providing such services. Management should make further improvements to reduce customer dissatisfaction on the mentioned topics.
Oman Air	Passenger satisfaction with the services of this airline is at a good level, however, most of the negative comments are about time delays and criticisms of the quality of services on topics such as "customer support" and "meal". These services need to be improved by the company to enhance customer satisfaction.
Saudia	Managers should pay more attention to passenger seat design, especially in economy class. Improving the quality of food served to passengers, and reducing service process delays are some other recommendations to the managers.
Gulf Air	Most of the complaints were about the quality of food served on the flights, along with the poor design of the passenger seat and the attitude of the stewards, which need to be reconsidered. Identifying the cause of customer dissatisfaction with stewardess services and training new customer communication skills to meet their needs during the flight is one of the ways to enhance customer satisfaction.
Kuwait Airways	In the field of "customer support" and "time" topics, the level of satisfaction is moderate, and in the topic of "meal", it is poor, which is a place for revision and improvement, especially in the field of nutrition. Paying attention to the taste of passengers on flights in some specific areas can be effective as a way to increase customer satisfaction.
Royal Jordanian Airlines	The main weaknesses of this airline services are mostly in the field of passenger comfort, time delays, and nutrition issues that need to be improved. It is recommended that the managers of this airline take appropriate decisions by quantitatively and qualitatively measuring customer satisfaction by focusing on the identified weaknesses.
Flydubai	The services provided in the "time", "cabin discussion" and "meal" topics have caused dissatisfaction among passengers that require to be reviewed. In other cases, the level of passenger satisfaction with the service is average.

6. Future research direction

For future research, the data from this work will be useful not only for managers, but also for airline customers by constructing a recommendation system to provide suggestions to passengers according to their expectations, desires, and purpose of their trips taking into account factors such as budget and destination.

Further studies could be conducted by considering the type of flight class (e.g., economy class, business class, first class) to identify different expectations of passengers to capture hidden semantic structure in opinions, this helps with a better understanding of customer needs for airline managers. The use of new topic modeling methods with information extraction approaches such as Deep Neural Networks or optimizing results would be another study option. While the focus of our study is on the airline industry, the findings of our study can be applied to any service-oriented companies, including hotel services and hospital services to identify what factors contribute to customer satisfaction. Also, providing a customer classification system can be a new idea to be used by company managers to meet the needs of different market segments and deliver quality services closer to customer demands.

Funding

This research did not receive any specific grants from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT author contribution statement

Siavash Farzadnia: Conceptualization, Methodology, Software, Formal analysis, Data Curation, Writing – Original Draft, Writing – Review & Editing. Iman Raeesi Vanani: Methodology, Investigation, Writing – Review & Editing, Supervision.

Data availability

Data will be made available on request.

References

Adeborna, E., Siau, K., 2014. An approach to sentiment analysis-the case of airline quality rating. PACIS 363.

Arora, S., Ge, R., Halpern, Y., Mimno, D., Moitra, A., Sontag, D., Wu, Y., Zhu, M., 2013. A practical algorithm for topic modeling with provable guarantees. International Conference on Machine Learning 280–288.

Arun, R., Suresh, V., Veni Madhavan, C.E., Murthy, N., 2010. On finding the natural number of topics with latent dirichlet allocation: some observations. Pacific-Asia Conference on Knowledge Discovery and Data Mining 391–402. https://doi.org/10.1007/978-3-642-13657-3_43.

Bastani, K., Namavari, H., Shaffer, J., 2019. Latent Dirichlet allocation (LDA) for topic modeling of the CFPB consumer complaints. Expert Syst. Appl. 127, 256–271. https://doi.org/10.1016/j.eswa.2019.03.001.

Bergamaschi, S., Po, L., 2014. Comparing LDA and LSA topic models for content-based movie recommendation systems. International Conference on Web Information Systems and Technologies 247–263. https://doi.org/10.1007/978-3-319-27030-2_16.

Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent dirichlet allocation. Jan J. Mach. Learn. Res. 3, 993–1022.

Chen, H.-T., Chao, C.-C., 2015. Airline choice by passengers from Taiwan and China: a case study of outgoing passengers from Kaohsiung International Airport. J. Air Transport. Manag. 49, 53–63. https://doi.org/10.1016/j.jairtraman.2015.08.002.

Cheng, X., Yan, X., Lan, Y., Guo, J., 2014. Btm: topic modeling over short texts. IEEE Trans. Knowl. Data Eng. 26 (12), 2928–2941. https://doi.org/10.1109/TKDE.2014.2313872.

Choi, K., 2017. Multi-period efficiency and productivity changes in US domestic airlines. J. Air Transport. Manag. 59, 18–25. https://doi.org/10.1016/j.jairtraman.2016.11.007.

Dolnicar, S., Grabler, K., Grün, B., Kulnig, A., 2011. Key drivers of airline loyalty. Tourism Manag. 32 (5), 1020–1026. https://doi.org/10.1016/j.tourman.2010.08.014.

Foltz, P.W., Gilliam, S., Kendall, S., 2000. Supporting content-based feedback in on-line writing evaluation with LSA. Interact. Learn. Environ. 8 (2), 111–127. https://doi.org/10.1076/1049-4820(200008)8:2;1-B;FT111.

Gitto, S., Mancuso, P., 2017. Improving airport services using sentiment analysis of the websites. Tourism Manag. Perspect. 22, 132–136. https://doi.org/10.1016/j.tmp.2017.03.008.

Greer, C.R., Lei, D., 2012. Collaborative innovation with customers: a review of the literature and suggestions for future research. Int. J. Manag. Rev. 14 (1), 63–84. https://doi.org/10.1111/j.1468-2370.2011.00310.x.

Gross, A., Murthy, D., 2014. Modeling virtual organizations with Latent Dirichlet Allocation: a case for natural language processing. Neural Network. 58, 38–49. https://doi.org/10.1016/j.neunet.2014.05.008.

Hanafizadeh, P., Paydar, N.R., 2013. A data mining model for risk assessment and customer segmentation in the insurance industry. Int. J. Strat. Decis. Sci. 4 (1), 52–78. https://doi.org/10.4018/jsds.2013010104.

Hong, J.-W., Park, S.-B., 2019. The identification of marketing performance using text mining of airline review data. Mobile Inf. Syst. https://doi.org/10.1155/2019/1790429, 2019.

Hong, L., Davison, B.D., 2010. Empirical study of topic modeling in twitter. Proceedings of the First Workshop on Social Media Analytics 80–88. https://doi.org/10.1145/1964858.1964870.

Hu, Y., Boyd-Graber, J., Satinoff, B., Smith, A., 2014. Interactive topic modeling. Mach. Learn. 95 (3), 423–469. https://doi.org/10.1007/s10994-013-5413-0.

Jeong, B., Yoon, J., Lee, J.-M., 2019. Social media mining for product planning: a product opportunity mining approach based on topic modeling and sentiment analysis. Int. J. Inf. Manag. 48, 280–290. https://doi.org/10.1016/j.ijinfomgt.2017.09.009.

Jiang, H., Zhang, Y., 2016. An investigation of service quality, customer satisfaction and loyalty in China's airline market. J. Air Transport. Manag. 57, 80–88. https://doi.org/10.1016/j.jairtraman.2016.07.008.

Jin, J., Liu, Y., Ji, P., Liu, H., 2016. Understanding big consumer opinion data for market-driven product design. Int. J. Prod. Res. 54 (10), 3019–3041. https://doi.org/10.1080/00207543.2016.1154208.

Korfiatis, N., Stamolampros, P., Kourouthanassis, P., Sagiadinos, V., 2019. Measuring service quality from unstructured data: a topic modeling application on airline passengers' online reviews. Expert Syst. Appl. 116, 472–486. https://doi.org/10.1016/j.eswa.2018.09.037.

Kuang, D., Choo, J., Park, H., 2015. Nonnegative matrix factorization for interactive topic modeling and document clustering. In: Partitional Clustering Algorithms. Springer, pp. 215–243. https://doi.org/10.1007/978-3-319-09259-1_7.

Kurtulmuşoğlu, F.B., Can, G.F., Pakdil, F., Tolon, M., 2018. Does gender matter? Considering gender of service in the airline industry. J. Air Transport. Manag. 70, 73–82. https://doi.org/10.1016/j.jairtraman.2018.04.011.

Lachnidaki, M., Grigoroudis, E., Zopounidis, C., 2021. Agro-tourism customer satisfaction analysis based on the theory of attractive quality. In: Interdisciplinary Perspectives on Operations Management and Service Evaluation. IGI Global, pp. 290–312. https://doi.org/10.4018/978-1-7998-5442-5.ch015.

Lacic, E., Kowald, D., Lex, E., 2016. High enough? explaining and predicting traveler satisfaction using airline reviews. Proceedings of the 27th ACM Conference on Hypertext and Social Media 249–254. https://doi.org/10.1145/2914586.2914629.

Lim, J., Lee, H.C., 2020. Comparisons of service quality perceptions between full service carriers and low cost carriers in airline travel. Curr. Issues Tourism 23 (10), 1261–1276. https://doi.org/10.1080/13683500.2019.1604638.

Medina-Muñoz, D.R., Medina-Muñoz, R.D., Suárez-Cabrera, M.Á., 2018. Determining important attributes for assessing the attractiveness of airlines. J. Air Transport. Manag. 70, 45–56. https://doi.org/10.1016/j.jairtraman.2018.01.002.

Mostafa, M.M., 2013. An emotional polarity analysis of consumers' airline service tweets. Social Network Analysis and Mining 3 (3), 635–649. https://doi.org/10.1007/s13278-013-0111-2.

Park, E., Jang, Y., Kim, J., Jeong, N.J., Bae, K., del Pobil, A.P., 2019. Determinants of customer satisfaction with airline services: an analysis of customer feedback big data. J. Retailing Consum. Serv. 51, 186–190. https://doi.org/10.1016/j.jretconser.2019.06.009.

Raeesi Vanani, I., 2017. Designing a predictive analytics for the formulation of intelligent decision making policies for VIP customers investing in the bank. J. Inf. Technol. Manag. 9 (3), 477–511. https://doi.org/10.22059/JITM.2017.216587.2144.

Raeesi Vanani, I., 2019. Text analytics of customers on twitter: brand sentiments in customer support. J. Inf. Technol. Manag. 11 (2), 43–58. https://doi.org/10.22059/JITM.2019.291087.2410.

Ravi, K., Ravi, V., 2015. A survey on opinion mining and sentiment analysis: tasks, approaches and applications. Knowl. Base Syst. 89, 14–46. https://doi.org/10.1016/j.knosys.2015.06.015.

Riaz, S., Fatima, M., Kamran, M., Nisar, M.W., 2019. Opinion mining on large scale data using sentiment analysis and k-means clustering. Cluster Comput. 22 (3), 7149–7164. https://doi.org/10.1007/s10586-017-1077-z.

Sohrabi, B., Vanani, I.R., Abedin, E., 2018. Human resources management and information systems trend analysis using text clustering. Int. J. Hum. Cap. Inf. Technol. Prof. (IJHCITP) 9 (3), 1–24. https://doi.org/10.4018/IJHCITP.2018070101.

Sohrabi, B., Vanani, I.R., Tahmasebipur, K., Fazli, S., 2012. An exploratory analysis of hotel selection factors: a comprehensive survey of Tehran hotels. Int. J. Hospit. Manag. 31 (1), 96–106. https://doi.org/10.1016/j.ijhm.2011.06.002.

Stevens, K., Kegelmeyer, P., Andrzejewski, D., Buttler, D., 2012. Exploring Topic Coherence over Many Models and Many Topics, pp. 952–961. Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning.

Suaysom, N., Gu, W., 2018. Expert opinion and coherence based topic modeling. International Journal on Natural Language Computing (IJNLC) 7. https://doi.org/10.2139/ssrn.3414903.

Sun, Y., Han, J., Gao, J., Yu, Y., 2009. itopicmodel: information network-integrated topic modeling. Ninth IEEE International Conference on Data Mining 493–502. https://doi.org/10.1109/ICDM.2009.43, 2009.

Teichert, T., Shehu, E., von Wartburg, I., 2008. Customer segmentation revisited: the case of the airline industry. Transport. Res. Pol. Pract. 42 (1), 227–242. https://doi.org/10.1016/j.tra.2007.08.003.

Tsafarakis, S., Kokotas, T., Pantouvakis, A., 2018. A multiple criteria approach for airline passenger satisfaction measurement and service quality improvement. J. Air Transport. Manag. 68, 61–75. https://doi.org/10.1016/j.jairtraman.2017.09.010.

Valdivia, A., Hrabova, E., Chaturvedi, I., Luzón, M.V., Troiano, L., Cambria, E., Herrera, F., 2019. Inconsistencies on TripAdvisor reviews: a unified index between users and sentiment analysis methods. Neurocomputing 353, 3–16. https://doi.org/10.1016/j.neucom.2018.09.096.

Vanani, I.R., Majidian, S., 2020. Meta-heuristic algorithms: a concentration on the applications in text mining. Big Data, IoT, and Machine Learning: Tools and Applications 113. https://doi.org/10.1201/9780429322990.

Vayansky, I., Kumar, S.A.P., 2020. A review of topic modeling methods. Inf. Syst. 94, 101582 https://doi.org/10.1016/j.is.2020.101582.