The University of Tehran Press

Interdisciplinary Journal of Management Studies (IJMS)
Home Page: https://ijms.ut.ac.ir

Online ISSN: 2981-0795

Validating and Confirming Crucial Service Quality Attributes to Airline Customers' Recommendations: A Feature Selection Approach

Dalianus Riantama

Department of Management, BINUS Business School Undergraduate Program, Bina Nusantara University, Jakarta , Indonesia. Email: dalianus.riantama@binus.ac.id

ARTICLE INFO

Article type:
Research Article

Article History:
Received 14 December 2022
Revised 28 July 2023
Accepted 11 September 2023
Published Online 12 June 2024

Keywords:
Airlines,
Customer recommendations,
Feature selection,
Online customer reviews,
Service quality.

ABSTRACT

Facing competitive market situations, customer recommendations are an essential tool to attract potential customers as well as to get free promotions. This study aims to measure the most important airline's service quality attributes of customer recommendations toward full-service and low-cost carrier airlines from Indonesia. To measure the most important airline's service quality attributes influencing customer recommendations, a feature selection approach was used. The performance of feature selection algorithms was evaluated using support vector machines (SVM). Findings revealed that airlines' reputation, employee knowledge, and information system were the most important airline service quality attributes of customer recommendations toward full-service airlines. On the other hand, airlines' reputation, employee knowledge, employee courteousness, on-time performance, safety & security, error records, responsive employees, and information systems were for low-cost carrier airlines. This research provides paths to airlines managers on how to get free advertisements through customer recommendations.

Cite this article: Riantama, D. (2024). Validating and Confirming Crucial Service Quality Attributes to Airline Customers' Recommendations: A Feature Selection Approach. *Interdisciplinary Journal of Management Studies* (*IJMS*), 17 (3), 889-906. DOI: http//doi.org/10.22059/ijms.2023.352483.675537

Publisher: University of Tehran Press.
DOI: http//doi.org/10.22059/ijms.2023.352483.675537

1. Introduction

The airline industry has expanded since the Second World War, reaching 4.1 billion passengers in 2017, and is expected to reach 10 billion passengers by 2040 (ICAO, 2017). However, airline profitability remains elusive and problematic as it is constantly hindered by high operating costs and massive competition (O'Connell et al., 2020). High operating costs may be influenced by massive monetary promotions and price wars (Oliveira & Caetano, 2019). Manuela et al. (2019) found that the increasing trend in the promotion and sales of airlines does not translate into a proportional increase in either passenger revenues or total operating revenues, resulting in lower net income. Those findings indicate that airlines are in demand to transform their current traditional promotional tools, which are monetary promotions, for example, price discounts, coupons, etc. (Manuela et al., 2019; Oliveira & Caetano, 2019). Marketing scholars have stated that monetary promotions tend to find positive effects on sales in the short term but undermining effects over the long term (Doob & al, 1969) as well as on the airline industry (Jeng & Lo, 2019). Similarly, recent research indicates that monetary promotions have a negative long-term impact on brand choice and attitude (Yi & Yoo, 2011). Indeed, if many of the new customers abandon and switch to competitors after the monetary promotion expires, the effort may not pay off in the long run (Reimers & Xie, 2019). Due to that, in the airline industry, Crespo-Almendros and Barrio-García (2016) confirmed that non-monetary online promotions are more likely to influence promotions' effectiveness than traditional monetary promotions.

One of the non-monetary online promotion tools is called customer recommendations in online customer reviews, which is free from cost because customers will do the promotions without getting paid. Researchers have confirmed that customer recommendations are a valuable tool to get airlines' promotions customers (Bogicevic et al., 2017; Siering et al., 2018). Potential airline' customers have a strong motivation to comply with experienced online passenger recommendations (Bigne et al., 2018). In addition, Nielsen (2014) showed that Indonesian digital consumers like to read customer recommendations in online customer reviews in advance if they want to buy flight tickets. BrightLocal (2017) also found that 85% of consumers trust personal recommendations when finalizing purchase decisions. It has been confirmed that customer recommendations in online customer reviews are crucial for airlines to attract potential customers.

However, the challenge is how an airline may identify the attributes that motivate customers to recommend the business to others. At the same time, prospective customers are interested in the attributes of the airline's services that encourage previous customers' positive recommendations to others. According to research, customer recommendations are significantly influenced by the service quality of the airline (Shah et al., 2020; Siering et al., 2018). But, given that they have high operating costs, airlines would like to prioritize their service attributes in order to cut costs because doing so allows them to devote enough resources to the most important service attributes while cutting back significantly on the least important service attributes (Idris & Naqshbandi, 2019).

In order to solve the challenge, one question is posed in this study: what are the most important airline service quality attributes that may affect customer recommendations? By answering that question, this study aims to find the most important airline service quality attributes that may influence customer recommendations. As a result, airlines can provide their service efficiently by knowing the most important service quality attributes to obtain promotion a result; airlines can provide their service efficiently by knowing the most important service quality attributes to obtain promotions from their customers.

Moreover, this study differently is different from previous research. Prior researchers, Koklic et al. (2017) have examined airline service quality attributes to understand customer recommendations, and they used the questionnaire survey. When compared to traditional questionnaires, online customer reviews allow us to obtain honest voices from customers because the reviews are produced by customers based on their willingness rather than the questions asked (Chen et al., 2020). As a result, this study employs online customer evaluations to identify the service quality attributes that influence consumer recommendations, and the results may be more accurate.

The rest of this article is divided into the following sections. This study begins by outlining the background of this investigation and pertinent literature. Next, utilizing a multimethod machine learning methodology, this study gathers online customer reviews and evaluates user recommendations. Finally, we go over the main conclusions and how they affect airlines.

2. Related Works

2.1. Airline Service Quality to Customer Recommendations

From its inception in the early 1980s to the present, the conceptual foundation of the service quality construct has been based on the maximum fulfillment of customer needs and the absolute matching of service quality with customer expectations (Peitzika et al., 2020). Airlines strive to improve service quality in order to provide customers with satisfactory services, prevent problems, and better identify problems (Bellizzi et al., 2018). Service quality in the airline industry also contributes to the attractiveness of the airline (Atalık et al., 2019). Kaura et al. (2015) have found a significant influence of service quality on customer behaviors, which is positive for business performance. Business performance could be affected by service quality because service quality can affect customer recommendations, which could impact prospective customers when they see it. When customers see a bad (not) from airline recommended by previous users, they will start to use another airline company. It has been approved by (Shah et al., 2020; Siering et al., 2018) that service quality is able to bring better recommendation behaviors by customers and get competitive advantages and benefits in the market.

Among other methods, the SERVQUAL dimension is a dependable and widely used approach to judging service quality in a variety of industries (Dinçer et al., 2019). This model was developed first by (Parasuraman et al., 1985) and is based on dimensions such as tangibles, dependability, responsiveness, assurance, and empathy. Initially, the SERVQUAL model recognized ten basic criteria by which consumers evaluate specific service quality attributes of a service: reliability, responsiveness, competence, access, courtesy, communication, credibility, security, customer understanding, and tangibility (Parasuraman et al., 1988). SERVQUAL has been used in a few studies for the service industry. Kayapınar and Erginel (2019) applied SERVQUAL to weigh the fuzzy weights of technical design necessities and to measure airport service quality. Shah et al. (2020) adopted SERVQUAL dimensions from the respondents in the international and domestic waiting lounges of Pakistan International Airlines. In addition, research in the service industry also confirmed that service quality as measured by the SERVQUAL scale is crucial due their the service industry also confirmed that service quality as measured by the SERVQUAL scale is crucial due to its strong association with service innovation (Tajeddini, 2011). Consequently, this research wants to know which attributes in SERVQUAL dimensions are the most important to customer recommendations through online customer reviews.

2.2. Online Customer Reviews

Nowadays, customers like to share their experiences after consuming hospitality and tourism services (Wu, 2022). Online reviews are very useful for airlines to comprehend their diverse customer base in order to bring service improvement strategies because airline sectors are inherently multicultural businesses (Ban & Kim, 2019).

Some previous research has applied to online reviews in terms of the airport and airline industry. Brochado et al. (2019) identified the main themes shared in online customer reviews by airline travelers and offered useful insights based on social media information. Sezgen et al. (2019) have investigated airline customers' satisfaction from customer reviews in Skytrax. Lucini et al. (2020) explore dimensions of airline customer satisfaction using online customer reviews and found it can provide airlines to redesign services that excel in those dimensions and are likely to improve the company's performance with customers.

2.3. Feature Selection

Data analysis, machine learning, and data mining all rely on feature selection (Chen et al., 2021). The feature selection or attribute reduction strategy solves the dimensionality reduction problem by governing a subset of original features and deleting irrelevant and redundant information in order to build a good model for classification or prediction tasks (Srikanta et al., 2021). The feature selection approach refers to the selection of a subset of the most important features from a feature set, which can be detrimental to specific activities (Chen et al., 2020). Feature selection is an effective method for removing redundant and irrelevant features, reducing model complexity, and improving model accuracy and generalization capability (Azizi et al., 2021; Jandaghi et al., 2021). Feature selection assists in data comprehension by reducing the effect of the curse of dimensionality, reducing computation requirements, and improving predictor performance, which allows data to be represented more effectively (Chandrashekar & Sahin, 2014; Tommasel & Godoy, 2018). Feature selection approaches can be categorized into three groups, namely wrappers, filters, and embedded approaches (Chen et al., 2020). Obviously, the embedded method, which is more effective than both the filter method and the wrapper method, automatically selects the useful features during the training process (Zheng et al., 2020). This method outperforms the wrapper and filter methods in over-fitting data (Sahran et al., 2018). The embedded method is commonly represented by the least absolute shrinkage and selection operator (LASSO), and supports vector machine recursive feature elimination (SVM-RFE).

2.3.1. Support Vector Machine Recursive Feature Elimination (SVM-RFE)

SVM-RFE was first proposed by (Guyon et al., 2002). SVM-RFE can reduce the feature dimension maintain while maintaining accuracy (Chen et al., 2021). SVM-RFE has been successfully used in many applications. Shao et al. (2017) built a new electricity price prediction strategy utilizing mutual information-based SVM-RFE. Sahran et al. (2018) employed the SVM-RFE feature selection method for diagnosing and grading prostate. Consequently, this study also employs SVM-RFE to do feature selection purpose to find the most important service quality attributes to customer recommendations.

2.3.2. Least Absolute Shrinkage Selection Operator (LASSO)

LASSO uses the penalty term to shrink the coefficients of certain features to zero to achieve feature selection. The regularization method proposed by (Tibshirani, 1996) does feature selection and regression simultaneously, which is popular in machine learning. Dastjerdi et al. (2019) employed LASSO to detect managers' fraud risk, and they found LASSO was more accurate than convex optimization (CVX). Chen et al. (2020) used LASSO and success to select the most important words for fast-food restaurants' customer satisfaction. Consequently, this study also employs LASSO to do feature selection purposes to find the most important service quality attributes to customer recommendations.

2.4. Support Vector Machines (SVM)

SVM is a supervised learning method proposed by (Cortes & Vapnik, 1995). SVM was found to be superior when the evaluation was performed for machine learning classifiers (Trivedi et al., 2018). Trivedi et al. (2018) employed SVM and was found to be powerful to do evaluate the performance of feature selection algorithms with the data source from movie reviews. Alirezanejad et al. (2020) employed SVM and proved that SVM could be a superior candidate for evaluating the classification accuracy of feature selection algorithms with the data from medical datasets. Consequently, this work uses SVM to examine the best feature selection algorithm with higher OA.

3. Research Methods

This section will introduce the implementation steps of the employed method in this study. The implementation procedure which described in the figure 1 could be divided into 8 steps. Concise descriptions of implementation are listed below.

3.1. Data Collection

This research collected online customer reviews of four Indonesian airline companies, shown in Table 1. The airlines are the biggest airlines in each service, which are full-service and low-cost carrier airlines. An open website, namely Skytrax (www.airlinequality.com), was used to collect review comments and recommendation ratings utilizing a web crawler. Skytrax is visited by about 1.26 million visitors per month, and 87.47 percent use terms like airline(s), air, and review-(s) (Messner, 2020). The comments on Skytrax were studied to be greatly accurate, seeing that a set of verification and security features were applied (Bogicevic et al., 2017). Song et al. (2020) used Skytrax to collect customers' comments to analyze airline passengers' emotions. Consequently, reviews and customer recommendation ratings posted in English were collected from Skytrax as samples in this research.

To make sure that the sample data could represent the majority of customers, Chiu & Lin (2018) stated that to obtain valid results, one study at least 50 samples of reviews. During the collection process, this study collected 1.025 reviews and recommendation ratings. The data was from April 14th, 2012 - Oct 6th, 2022.

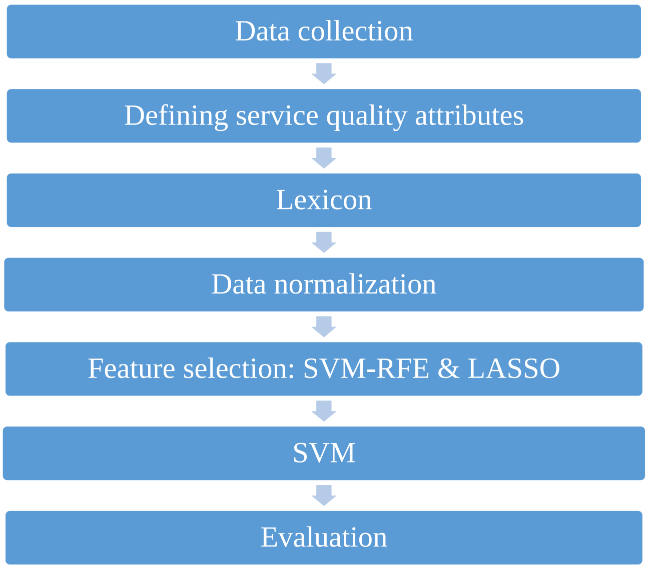

Fig. 1. The implemental procedure of the employed feature selection approach for discovering airlines' customer recommendations

Table 1. Summary of Collected Data

Number of airlines	Type of Airline	Total of Reviews
2	Full-service Airline	846
2	Low-cost Carrier Airline	179

3.2. Defining service quality attributes

This study used SERVQUAL to measure customer recommendations. SERVQUAL was developed to attain a more reliable measure (Parasuraman et al., 1988; Shah et al., 2020). This approach aims to measure customer expectations and perceptions, which can result in customer recommendations (Bogicevic et al., 2017). Another factor developed by the authors is website quality because the rapid growth of web 2.0 communication channels is a part of service quality. Tarkang et al. (2020) stated that the website quality has a high possibility of being recommended by the airlines to friends. Table 2 lists the service quality attributes which may influence customer recommendations.

Table 2. Defining service quality attributes

Attributes (Annotation)	Definition	Items	Adapted from
Tangibles (TA)	Appearance, physical facilities, equipment and personnel.	TA1: Crew Appearance (employees, presentable, appearance, etc) TA2: Aircraft Facilities and Looks (clean, cabin, modern etc)	(Atalay et al., 2019) (Jeeradist et al., 2016) (Rajaguru, 2016)
Reliability (RE)	Capability to execute the promised service credibility and dependably.	RE1: On-time performance (timeliness, certain, accurate) RE2: Safety and Security (security, safety, etc) RE3: Error records (cancelation, errors, etc)	(Atalay et al., 2019) (Jeeradist et al., 2016) (Perçin, 2018) (Rajaguru, 2016)
Responsiveness (RS)	Enthusiasm to help customers and grant precise service.	RS1: Responsive Employee (Responsiveness, prompt, etc) RS2: Willingness to Help (willing, busy, etc)	(Jeeradist et al., 2016) (Rajaguru, 2016)
Assurance (AS)	Propriety of crew and their capability to deliver confidence and trust.	AS1: Reputation Airline (reputation, confidence, etc) AS2: Employee Knowledge (skill, knowledge, etc) AS3: Employee Courteousness (courteousness, polite, etc)	(Atalay et al., 2019) (Basfirinci & Mitra, 2015) (Jeeradist et al., 2016) (Rajaguru, 2016)
Empathy (EM)	Care about individual attention that airlines grant to customers.	EM1: Personal Attention (attention, interest, specific, personal, etc) EM2: Understand Customer Needs (need, handling, schedule, ticketing etc)	(Basfirinci & Mitra, 2015) (Jeeradist et al., 2016) (Rajaguru, 2016)
Website Quality (WE)	passengers are easier to get information and reviewing	WE1: Information system (Information, news, etc) WE2: Complain system (critics, gratitude, reviews, etc)	Constructed by this work

3.3. Lexicon

After the service quality attributes had been revealed, a lexicon was built implementing word frequency computation using QDA Miner® to the collected reviews which are related to the SERVQUAL dimension that was adapted based on the literature review. Another factor was developed by the authors, namely, website quality. In the airline industry, there is a need for the SERVQUAL dimension with some modifications suggested to use the most updated salient service quality attributes (Hussain et al., 2015). Then, based on the literature review, related words of SERVQUAL were collected by synonyms and antonyms from thesaurus.com to build the entire service quality attributes lexicons.

The use of a part-of-speech (POS) tagger to annotate nouns and noun phrases for online customer reviews is one of the most common techniques for detecting service attributes (Hu & Trivedi, 2020). In this study, nouns were used as POS to identify all relevant factor attributes. POS terms include adverbs, verbs, and adjectives, which can represent customers' feelings about their opinions, ideas, reactions, and emotions (Gao et al., 2018; Littman & Turney, 2003).

3.4. Data normalization

To obtain valid results from the feature selection method, the data had to be reformatted beforehand. Equation (1) was used in this study to normalize the data into the interval (-1,1).

$$v' = \frac{v - min_a}{max_a - min_a} \tag{1}$$

Aside from data normalization, a five-fold cross-validation experiment would be carried out. The data will be split into five equal parts. Four parts served as training data sets, while one served as a test data set. Furthermore, this study conducted five-fold cross-validation experiments.

3.5. Feature Selection

The important service quality attributes were discovered using two feature selection methods, SVM-RFE and LASSO. If one factor is deemed important, it must appear at least five times in the five-fold experiments. The explanations for each algorithm are as follows.

3.5.1. SVM-RFE

Weka® software was used to run SVM-RFE after the lexicon was established. The primary goal of SVM-RFE is to compute ranking weights for all features and sort them using weight vectors as the classification basis. SVM-RFE is a backward feature removal iteration process.

The steps for selecting a feature set are shown below.

(1) Train the classifier using the current dataset.

(2) Determine the ranking weights for each feature.

(3) Remove the feature with the

Iterate until only one feature remains in the dataset; the implementation result provides a list of features in descending order of weight. The algorithm will remove the feature with the lowest ranking weight while keeping the feature variables with the greatest impact. Finally, the feature variables will be listed in descending order based on the degree of explanatory difference. The selection of feature sets by SVM-RFE can be divided into three steps: (1) the input of the datasets to be classified, (2) the calculation of the weight of each feature, and (3) the deletion of the feature with the lowest weight to obtain the feature ranking. The computational step is depicted below (Chen et al., 2021).

Inputs:

Training examples

$$X_0 = [\, x_1, x_2, \ldots x_k, \ldots x_l \,]^T$$

Class labels

$$y = [\, y_1, y_2, \ldots y_k, \ldots y_l \,]^T$$

Feature Sorting:

The current feature set

$$s = [1, 2, ..n]$$

Feature sorted list

$$r = []$$

Repeat the following process until

$$s = []$$

To obtain the new training sample matrix according to remain features

$$X = X_0(:, s)$$

Training classifier

$$\propto = SVM - train(X, y)$$

Compute the weight vector of dimension length(s)

$$w = \sum_k \propto_k y_k x_k$$

Compute the ranking criteria

$$c = (\mathrm{w_i})^2 \text{, for all i}$$

Find the feature with smallest ranking criterion

$$f = \arg\min(c)$$

Update feature ranked list

$$r = [s(f), r]$$

Remove the feature with smallest ranking criterion

$$s = s(1 : f - 1, f + 1 : length(s))$$

Output:

Ranked feature list r. In each loop, the feature with the smallest $(w_i)^2$ will be removed. After that, the SVM retrains the remaining features to achieve the new feature sorting. SVM-RFE repeats the process until a feature-sorted list is obtained. We can obtain the best feature subsets by training SVM with the sorted list's feature subsets and evaluating them with the SVM prediction accuracy.

SVM-RFE is suggested for selecting features that are used in a variety of situations, such as marketing (Shieh & Yang, 2008) or medicine (Adnane et al., 2012). In this study, it is suggested that features be selected using online user reviews. Working with a high number of features is possible with SVM-RFE without the need for any statistical correction. Additionally, this method accounts for the impact of individual variances by eliminating useless or extreme data. Consequently, this study also employs SVM-RFE to do feature selection purposes to find the most important service quality attributes to customer recommendations.

3.5.2. LASSO

Matlab® software was used to run LASSO after the lexicon was established. It used regression and feature selection functions at the same time to extract the significant features, as shown in equation (3), where x is the explanatory variable, T is the number of data, and λ is the adjustment system.

$$\min = \sum_{t=1}^{T} (\mathrm{y_t} - \beta_0 - \beta_1 \mathrm{x_{1,t}} - \ldots - \beta_k \mathrm{x_{k,t}})^2, \quad \text{s.t.} \sum_{j=1}^{k} |\beta_j| \leq \tag{2}$$

In equation (2), a regression parameter value namely βi is limited by a specific penalty selection benchmark, and afterward, the suitable variables are chosen. Given a k-explained transformation, the parameter estimate '\hat{\beta}' is influenced by the value of λ. When the λ's value approaches infinity, the estimate of parameter \hat{\beta} is not limited, and the estimate is the value determined by the least-squares method. The contrary situation is when the λ is adjusted to 0, all parameter estimates become 0. As the result, it provides a feature subset according to the coefficient zero or not to be a criterion for choosing service quality attributes.

LASSO generates a more refined model by generating a valve function, decreasing the sum of coefficients using the square of the least square approach, and compressing the sum of absolute coefficient values to less than the constant (Chen et al., 2021). LASSO has several advantages. First, LASSO is used to reduce the variation of the slope coefficients without significantly increasing the bias (Lee & Cai, 2020). Reduce the dimensionality of the production model to reduce the estimator's variance. Second, LASSO chooses fewer variables to improve the predicted function's accuracy and reduce over-fitting (Elyasiani et al., 2019). LASSO, on the other hand, has one drawback: it can only capture linear relationships (He et al., 2019). It is important to remember, however, that linear and nonlinear models have trade-offs. Linear models may fail if they are unable to capture nonlinear relationships. The calibration of nonlinear models is difficult due to the small number of samples. For choosing features that are applied in a range of contexts, such as marketing (Wu, 2022) or architecture (Parzinger et al., 2022), LASSO is recommended. Consequently, this study also employs LASSO to do feature selection purposes to find the most important service quality attributes to customer recommendations.

3.6. SVM

The experimental feature selection algorithms SVM-RFE and LASSO results are evaluated using SVM. SVM will be used to evaluate the selected feature subsets. LibSVM is used to train classifiers from original service quality attributes and feature subsets that have been chosen. LIBSVM, an effective open-source library tool that supports multi-class classification, is used to create the SVM classifier (Wang et al., 2019). The C-SVM classification parameter selection tool grid.py in the Radial Basis Function (RBF) is used to get the optimal parameters settings (D. Zhao et al., 2019). The phases are mentioned:

Phase 3.5.1: Normalize the input data.

Phase 3.5.2: Transform data format.

Phase 3.5.3: Apply the RBF kernel function listed in equation (3)

$$K\left(x,y\right)=e^{-rx-y^{2}} \tag{3}$$

Phase 3.5.4: Apply cross-validation to select the best parameters C and γ.

Phase 3.5.5: Get the best parameters C and γ, and train SVM.

Phase 3.5.6: Test with the constructed model.

3.7. Evaluation

The confusion matrix has traditionally been used to judge classification performance in terms of performance evaluation. A confusion matrix is a summary of the results of classification task prediction (S. Zhang & Duan, 2018). The number of incorrect and correct predictions, summarized with count values and separated by class, is the key to the confusion matrix. In this study, we use overall accuracy (OA) to determine which features are most important to the model. The excellent OA of the proposed method demonstrates that feature selection and representation capture useful information (Chen et al., 2021). The better the model's features, the higher the OA score.

$$\text{Overall Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FP}+\text{TN}+\text{FN}} \tag{4}$$

4. Experimental Results

4.1. Feature Selection Results

4.1.1. SVM-RFE

SVM-RFE does a feature selection approach and then we pick up the service quality attributes that appear the most based on the word occurrence frequency by a five-fold cross-validation experiment. As usual, the occurrence service quality attributes may appear 5 times, 4 times, and so on, but at this time the whole service quality attributes have been picked it up as important service quality attributes to the model and appeared 5 times either to the first data set or the second data set, so to another feature selection algorithm, we will choose 5 times appearance. With a five-fold cross-validation experiment approach, the results were also obtained five results as shown in the table 3 and 4. In addition, figure 2 and 3 presented the finding example of SVM-RFE for fold 1.

Figure 2 presented the example of running result of fold 1 for full-service airlines which the Weka® software showed that the selected attributes was 14 which is the whole attributes in this study. The process will be the same for the rest of the folds.

```
=== Attribute Selection on all input data ===

Search Method:
        Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 15 Y):
        ReliefF Ranking Filter
        Instances sampled: all
        Number of nearest neighbours (k): 10
        Equal influence nearest neighbours

Ranked attributes:
 0.021556  13 WE1
 0.012406   8 RE3
 0.01044    7 RE2
 0.008298  14 WE2
 0.008291   9 RS1
 0.005989   2 AS2
 0.005968  10 RS2
 0.004947   6 RE1
 0.002942   4 EM1
 0.001702   5 EM2
-0.000162  11 TA1
-0.001178   1 AS1
-0.003314  12 TA2
-0.006716   3 AS3

Selected attributes: 13,8,7,14,9,2,10,6,4,5,11,1,12,3 : 14
```

Fig. 2. Example of the fold 1 SVM-RFE results for full-service airlines

Table 3. Selected service quality attributes by SVM-RFE from full-service airlines

Frequency	Fold1	Fold2	Fold3	Fold4	Fold5
5	WE1	WE1	WE1	WE1	WE1
	RE3	RE3	RE3	RE3	RE3
	RE2	RE2	RE2	RE2	RE2
	WE2	WE2	WE2	WE2	RS1
	RS1	RS1	RS1	RS1	WE2
	AS2	RS2	RS2	RS2	RS2
	RS2	AS2	AS2	AS2	AS2
	RE1	RE1	RE1	RE1	RE1
	EM1	EM1	EM1	EM1	EM1
	EM2	EM2	EM2	EM2	EM2
	TA1	TA1	TA1	TA1	TA1
	AS1	AS1	AS1	AS1	AS1
	TA2	TA2	TA2	TA2	TA2
	AS3	AS3	AS3	AS3	AS3

SVM-RFE selected among 14 original service quality attributes as shown in the table 3, and it is found that the whole 14 original service quality attributes are significant influence on customer recommendations for full-service airlines, therefore the 14 service quality attributes will be evaluated by SVM for further analysis.

Figure 3 presented the example of running result of fold 1 for low-cost carrier airlines which the Weka® software showed that the selected attributes was 14 which is the whole attributes in this study. The process will be the same for the rest of the folds.

```
=== Attribute Selection on all input data ===

Search Method:
        Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 15 Y):
        ReliefF Ranking Filter
        Instances sampled: all
        Number of nearest neighbours (k): 10
        Equal influence nearest neighbours

Ranked attributes:
 0.021556  13 WE1
 0.012406   8 RE3
 0.01044    7 RE2
 0.008298  14 WE2
 0.008291   9 RS1
 0.005989   2 AS2
 0.005968  10 RS2
 0.004947   6 RE1
 0.002942   4 EM1
 0.001702   5 EM2
-0.000162  11 TA1
-0.001178   1 AS1
-0.003314  12 TA2
-0.006716   3 AS3

Selected attributes: 13,8,7,14,9,2,10,6,4,5,11,1,12,3 : 14
```

Fig. 3. Example of the fold 1 SVM-RFE results for low-cost carrier airlines

Table 4. Selected service quality attributes by SVM-RFE from low-cost carrier airlines

Frequency	Fold1	Fold2	Fold3	Fold4	Fold5
5	RE3	RE3	RE3	RE3	RE3
	TA1	TA1	TA1	TA1	TA1
	AS1	AS1	AS1	AS1	AS1
	AS2	AS2	AS2	AS2	AS2
	EM1	EM1	EM1	EM1	EM1
	RE2	RE2	RE2	RE2	RE2
	RS2	RS2	RS2	RS2	RS2
	WE2	WE2	WE2	WE2	WE2
	TA2	TA2	TA2	TA2	TA2
	AS3	AS3	AS3	AS3	AS3
	WE1	WE1	WE1	WE1	WE1
	RE1	RE1	RE1	RE1	RE1
	EM2	EM2	EM2	EM2	EM2
	RS1	RS1	RS1	RS1	RS1

SVM-RFE selected among 14 original service quality attributes as shown in table 4, and it is found that the whole 14 original service quality attributes are a significant influence on customer recommendations for low-cost carrier airlines, therefore the 14 service quality attributes will be evaluated by SVM for further analysis.

4.1.2. LASSO Results

To filter out the important attributes in the LASSO parameter setting, built-in Matlab® functions were used. It would set the regression coefficients of some words to zero, implying that these words are irrelevant to the regression model (Zhao & Yu, 2006). Simply, phrases with 0 regression coefficients were deemed unimportant in terms of influencing consumer recommendations. On the other hand, words having non-zero regression coefficients can be regarded as important attributes for influencing consumer recommendations (Zhang & Huang, 2008). The dataset was divided into five equivalent portions since the five-fold cross-validation experiment approach was used. Each of the five components was run using a different LASSO parameter setting. With a five-fold cross-validation experiment approach, the results were also obtained five results as shown in the table 5 and 6. In addition, figure 4 and 5 presented the finding example of LASSO for fold 1.

The running result of fold 1 for full-service airlines was shown in Figure 4, and Matlab® software indicated that the total selected number of attributes in this study was 3. The process will be the same for the rest of the folds.

LASSO found that there are three service quality attributes that are more significant to influence customer recommendations which are AS1, AS2, and WE1 for full-service airlines as shown in table 5. For further analysis, these three service quality attributes are going to be evaluated by SVM.

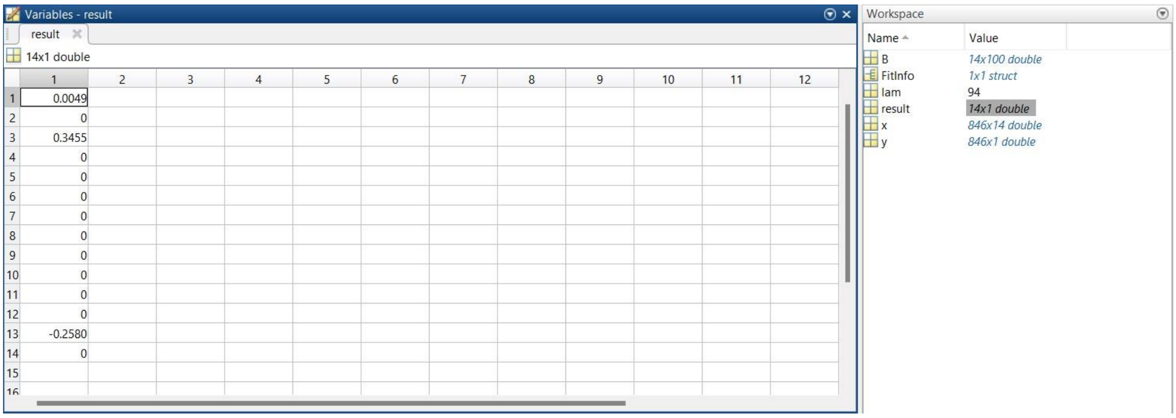

Fig. 4. Example of the fold 1 LASSO results for full-service airlines

Table 5. Selected service quality attributes by LASSO from full-service airlines

Frequency	Attributes	Fold1	Fold2	Fold3	Fold4	Fold5
5	AS1	0.004879	0.102936	0.054506	0.148422	0.238832
	AS3	0.345457	0.409498	0.379096	0.437998	0.50513
	WE1	-0.25803	-0.39512	-0.3327	-0.44967	-0.52714

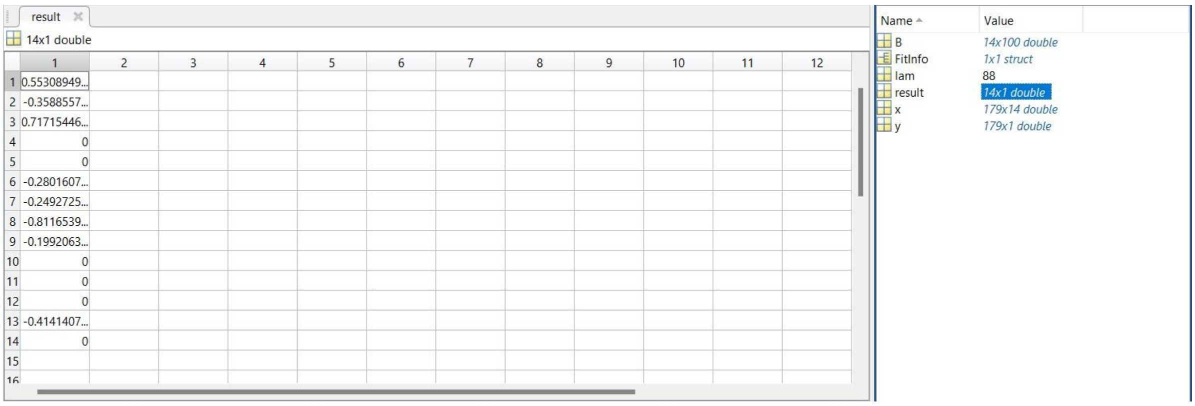

Fig. 5. Example of the fold 1 LASSO results for low-cost carrier airlines

The running result of fold 1 for low-cost airlines was shown in Figure 5, and Matlab® software indicated that the total selected number of attributes in this study was 8. The process will be the same for the rest of the folds.

Table 6. Selected service quality attributes by LASSO from low-cost carrier airlines

Frequency	Attributes	Fold1	Fold2	Fold3	Fold4	Fold5
5	AS1	0.553089	0.271536	0.495863	0.355391	0.271536
	AS2	-0.35886	-0.16992	-0.31556	-0.22249	-0.16992
	AS3	0.717154	0.594267	0.705521	0.647987	0.594267
	RE1	-0.28016	-0.1988	-0.25229	-0.20911	-0.1988
	RE2	-0.24927	-0.13354	-0.2215	-0.16615	-0.13354
	RE3	-0.81165	-0.60078	-0.76159	-0.65819	-0.60078
	RS1	-0.19921	-0.12972	-0.18202	-0.14403	-0.12972
	WE1	-0.41414	-0.3562	-0.40085	-0.36921	-0.3562

LASSO found that there are eight service quality attributes that are more significant to influence customer recommendations which are AS1, AS2, AS3, RE1, RE2, RE3, RS1, and WE1 for low-cost carrier airlines as shown in table 6. For further analysis, these eight service quality attributes are going to be evaluated by SVM.

5. Discussion

Table 7 presents the SVM evaluation for full-service airlines with LASSO having higher accuracy which is 87.48% than SVM-RFE at 87.14% and the original service quality attributes at 87.14%. This means 3 service quality attributes (AS1, AS3, and WE1) have a more significant influence on customer recommendations than 14 service quality attributes.

Table 8 presents the SVM evaluation for low-cost carrier airlines with LASSO having higher accuracy which is 60.33% than SVM-RFE at 58.05% and the original service quality attributes at 58.05%. This means 8 service quality attributes (AS1, AS2, AS3, RE1, RE2, RE3, RS1, and WE1) have a more significant influence on customer recommendations than 14 service quality attributes.

Table 7. SVM Evaluation of Full-Service Airlines

	LASSO (3 Attributes)	SVM-RFE (14 Attributes)	Original (14 Attributes)
Overall Accuracy (OA)	**87.48%**	87.14%	87.14%
Time	0.05	0.05	0.05

Table 8. SVM Evaluation of Low-Cost Carrier Airlines

	LASSO (8 Attributes)	SVM-RFE (14 Attributes)	Original (14 Attributes)
Overall Accuracy (OA)	**60.33%**	58.05%	58.05%
Time	0.03	0.03	0.03

Based on the results of the SVM evaluation this study selects the results of LASSO to represent the most important service quality attributes to customer recommendation of either full-service airlines or low-cost carrier airlines, so this study found that customers of full-service airlines care the most about Reputation Airline (AS1), Employee Knowledge (AS2), Information system (WE1) to recommend the airlines to others. On the other side, low-cost carrier customers focus the most on service quality attributes which are Reputation Airline (AS1), Employee Knowledge (AS2), Employee Courteousness (AS3), On-time performance (RE1), Safety and Security (RE2), Error records (RE3), Responsive Employee (RS1), Information system (WE1).

Reputation airline, employee knowledge, and information system were found as the most important attributes for customer recommendations for full-service airlines. When an airline has a good reputation, customers are more ready to spend extra to fly on it (Graham & Bansal, 2007) and recommend the airline to others (Vlachos & Lin, 2014). Airline service quality, especially personnel knowledge, has an impact on passengers' intentions to repurchase tickets and recommend the airline to others (Park et al., 2004). The development of information systems has opened up new possibilities for building strong personal connections between passengers and airlines, which influences passengers' willingness to recommend the airline to their friends (Bejou & Palmer, 1998). This result suggests that the higher reputation of airlines, employee knowledge, and information system lead to customer recommendations. Thus, improving the higher reputation of airlines, employee knowledge, and information system is crucial to encourage the willingness of customers to recommend full-service airlines to others.

For low-cost carrier airlines, including three attributes found for full-service airlines, there are five more attributes that are important to customer recommendations: employee courteousness, on-time performance, safety and security, error records, and responsiveness. Airline service quality, particularly employee courteousness, has an impact on passengers' intentions to repurchase tickets and recommend the airline to others (Park et al., 2004). On-time performance affects customer recommendations (Tansitpong, 2020). Safety and security are positively correlated with customer satisfaction, making it more likely that they will use that airline again or recommend it to others (Clemes et al., 2008). Minimum errors of some service attributes affect recommendation likelihood

(Halpern & Mwesiumo, 2021). the responsiveness aspect of service quality increases customer satisfaction and increases the possibility that they will recommend the airline to others (Abdullah et al., 2007). Thus, improving the reputation of the airline, employee knowledge, employee courteousness, on-time performance, safety and security, responsive employee and information system, and diminishing error records are crucial to encourage the willingness of customers to recommend the full-service airlines to others.

According to Siering et al. (2018), the most important factors influencing consumer recommendations for full-service airlines are seat comfort, safety, and punctuality. Those conclusions contrast sharply with the findings of this study, which focus on airline reputation, employee knowledge, and information systems. This could happen because Indonesian passengers have lost trust in Indonesian airlines as a result of some catastrophes. Therefore, passengers are very picky about a good airline's reputation, employee knowledge, and information system, making it worthwhile to pay more for a full-service airline.

Furthermore, Siering et al. (2018) discovered that the most important factors influencing consumer recommendations for low-cost carrier airlines are ground service, cabin personnel service, food & beverages, in-flight entertainment, and wifi & internet. These conclusions differ significantly from the findings of this study, which include airlines' reputation, employee knowledge, employee courteousness, on-time performance, safety & security, error records, responsive employees, and information systems. Following some mishaps in Indonesia, mostly involving low-cost carrier flights, passengers would focus solely on selecting low-cost carrier airlines with solid core services and demanding more good service than full-service airlines. It differs significantly from the findings of (Siering et al., 2018), which focus on augmented airline service.

6. Conclusions

This study develops a feature selection approach to understand customers' experience of the airline service quality and to know why customers are willing to recommend the airline. The study's findings show that low-cost carrier airlines' customers select more attributes than full-service airlines' customers to give their recommendations. This may occur because in Indonesia, low-cost carrier airlines had more records of service failure (Wahyuni TD & Fernando, 2016), so airline customers in Indonesia have more demand for low-cost carrier airlines.

This study also shows that feature selection methods are needed to deal with big data sets. Feature selection algorithms can also improve the OA, which is valuable for getting better features for the model. Feature selection provides an effective way to reduce model complexity and improve the accuracy and generalization capability of the model (Mirzaei et al., 2020).

7. Implications

7.1. Academic Implications

This study adds to the current literature on customer recommendation in three areas that distinguish it from similar studies. Firstly, it examines the direct influence of service quality attributes on customer recommendations. Secondly, it contends that using a feature selection algorithm has a stronger impact in determining the most significant service quality attributes of customer recommendations. Thirdly, it presents a research approach in the airline business based on a feature selection approach, which has not been used in earlier studies.

7.2. Practical Implications

This research makes various contributions to practice. To begin, full-service and low-cost carrier airline management may prioritize adorning the airline brand image in order to improve the airline's reputation. Employees must also be trained to improve their service knowledge. Then, in order to give information to passengers effectively and efficiently, the information system must be upgraded.

In addition, for low-cost carrier airlines, managers must push their personnel to be more respectful while engaging with passengers. The problem of flight punctuality must be tackled with an appropriate timetable. When performing services, safety and security must be double-checked. Managers are also accountable for ensuring that no further mistake records are obtained. When passengers require assistance, employees must be quick to respond.

Finally, this study may help airline executives prioritize their service offerings. The outcomes of this study can be used by airline executives to determine their service priorities in order to better serve their consumers. Sorting service priorities reduces service operation costs because the organization can employ fewer resources to satisfy the service quality features that customers value the most (Wu, 2022). Aside from cost efficiency in service operations, satisfying the important service quality attributes for customer recommendations can serve as a marketing tool for airlines because when the service quality attributes are met, customers will recommend the airlines to others, thereby promoting the airlines.

8. Research Limitation and Future Research

Future research should address many issues to improve the approach's applicability. Firstly, it's important to confirm if the results may be applied to other nations outside Indonesia. Future research should investigate whether the proposed approach's applicability may be used in other countries. Secondly, results showed that there is no significant difference in terms of time consumption even though this study uses feature selection algorithms compared to the original service quality attributes. Furthermore, it is important to collect much more data to clearly look at the differences in time. Thirdly, it is necessary to use more feature selection algorithms instead of LASSO and SVM-RFE so it could get more representative service quality attributes with better overall accuracy.

References

Abdullah, K., Manaf, N. H. A., & Noor, K. M. (2007). Measuring the service quality of airline services in Malaysia. *IIUM Journal of Economics and Management IIUM Journal of Economics & Management*, *15*(1), 1–29.

Adnane, M., Jiang, Z., & Yan, Z. (2012). Sleep-wake stages classification and sleep efficiency estimation using single-lead electrocardiogram. *Expert Systems with Applications*, *39*(1), 1401–1413. https://doi.org/10.1016/j.eswa.2011.08.022

Alirezanejad, M., Enayatifar, R., Motameni, H., & Nematzadeh, H. (2020). Heuristic filter feature selection methods for medical datasets. *Genomics*, *112*(2), 1173–1181. https://doi.org/10.1016/j.ygeno.2019.07.002

Atalay, K. D., Atalay, B., & Isin, F. B. (2019). FIPIA with information entropy: A new hybrid method to assess airline service quality. *Journal of Air Transport Management*, *76*, 67–77. https://doi.org/10.1016/j.jairtraman.2019.02.004

Atalık, Ö., Bakır, M., & Akan, Ş. (2019). The Role of In-Flight Service Quality on Value for Money in Business Class: A Logit Model on the Airline Industry. *Administrative Sciences*, *9*(1), 1–15. https://doi.org/10.3390/admsci9010026

Azizi, Z., Abdolvand, N., Asl, H. G., & Harandi, S. R. (2021). The Impact of Persian News on Stock Returns Through Text Mining Techniques. *Iranian Journal of Management Studies*, *14*(4), 331–346. https://doi.org/10.22059/IJMS.2021.295478.673915

Ban, H. J., & Kim, H. S. (2019). Understanding customer experience and satisfaction through airline passengers' online review. *Sustainability*, *11*(15), 4066. https://doi.org/10.3390/su11154066

Basfirinci, C., & Mitra, A. (2015). A cross cultural investigation of airlines service quality through integration of Servqual and the Kano model. *Journal of Air Transport Management*, *42*, 239–248. https://doi.org/10.1016/j.jairtraman.2014.11.005

Bejou, D., & Palmer, A. (1998). Service failure and loyalty: An exploratory empirical study of airline customers. *Journal of Services Marketing*, *12*(1), 7–22. https://doi.org/10.1108/08876049810202339

Bellizzi, M. G., Eboli, L., Forciniti, C., & Mazzulla, G. (2018). Air Transport Passengers' Satisfaction: An Ordered Logit Model. *Transportation Research Procedia*, *33*, 147–154. https://doi.org/10.1016/j.trpro.2018.10.087

Bigne, E., Andreu, L., Hernandez, B., & Ruiz, C. (2018). The impact of social media and offline influences on consumer behaviour. An analysis of the low-cost airline industry. *Current Issues in Tourism*, *21*(9), 1014–1032. https://doi.org/10.1080/13683500.2015.1126236

Bogicevic, V., Yang, W., Bujisic, M., & Bilgihan, A. (2017). Visual Data Mining: Analysis of Airline Service Quality Attributes. *Journal of Quality Assurance in Hospitality and Tourism*, *18*(4), 509–530. https://doi.org/10.1080/1528008X.2017.1314799

BrightLocal. (2017). *Local Consumer Review Survey 2017*. https://www.brightlocal.com/research/local-consumer-review-survey-2017/

Brochado, A., Rita, P., Oliveira, C., & Oliveira, F. (2019). Airline passengers' perceptions of service quality: themes in online reviews. *International Journal of Contemporary Hospitality Management*, *31*(2), 855–873. https://doi.org/10.1108/IJCHM-09-2017-0572

Chandrashekar, G., & Sahin, F. (2014). A survey on feature selection methods. *Computers and Electrical Engineering*, *40*, 16–28. https://doi.org/10.1016/j.compeleceng.2013.11.024

Chen, M. Y., Chang, J. R., Chen, L. S., & Shen, E. L. (2021). The key successful factors of video and mobile game crowdfunding projects using a lexicon-based feature selection approach. *Journal of Ambient Intelligence and Humanized Computing*, 1–19. https://doi.org/10.1007/s12652-021-03146-4

Chen, W.-K., Riantama, D., & Chen, L.-S. (2020). Using a Text Mining Approach to Hear Voices of Customers from Social Media toward the Fast-Food Restaurant Industry. *Sustainability*, *13*(1), 268. https://doi.org/10.3390/su13010268

Chen, W. K., Chen, L. S., & Pan, Y. T. (2021). A text mining-based framework to discover the important factors in text reviews for predicting the views of live streaming. *Applied Soft Computing*, *111*. https://doi.org/10.1016/j.asoc.2021.107704

Chiu, M. C., & Lin, K. Z. (2018). Utilizing text mining and Kansei Engineering to support data-driven design automation at conceptual design stage. *Advanced Engineering Informatics*, *38*, 826–839. https://doi.org/10.1016/j.aei.2018.11.002

Clemes, M. D., Gan, C., Kao, T. H., & Choong, M. (2008). An empirical analysis of customer satisfaction in international air travel. *Innovative Marketing*, *4*(2), 50–62.

Cortes, C., & Vapnik, V. (1995). Support-Vector Networks. *Machine Learning*, *20*, 273–297. https://doi.org/10.1023/A:1022627411411

Crespo-Almendros, E., & Barrio-García, S. Del. (2016). Online airline ticket purchasing: Influence of online sales promotion type and Internet experience. *Journal of Air Transport Management*, *53*, 23–34. https://doi.org/10.1016/j.jairtraman.2016.01.004

Dastjerdi, A. R., Foroghi, D., & Kiani, G. H. (2019). Detecting manager's fraud risk using text analysis: evidence from Iran. *Journal of Applied Accounting Research*, *20*(2), 154–171. https://doi.org/10.1108/JAAR-01-2018-0016

Dinçer, H., Yüksel, S., & Martínez, L. (2019). Analysis of balanced scorecard-based SERVQUAL criteria based on hesitant decision-making approaches. *Computers and Industrial Engineering*, *131*, 1–12. https://doi.org/10.1016/j.cie.2019.03.026

Doob, A. N., & al, E. (1969). Effect of initial selling price on subsequent sales. *Journal of Personality and Social Psychology*, *11*(4), 345–350. https://doi.org/10.1037/h0027415

Elyasiani, E., Jia, J., & Movaghari, H. (2019). Determinants of dividend payout and dividend propensity in an emerging market, Iran: an application of the LASSO. *Applied Economics*, *51*(42), 4576–4596. https://doi.org/10.1080/00036846.2019.1593315

Gao, S., Tang, O., Wang, H., & Yin, P. (2018). Identifying competitors through comparative relation mining of online reviews in the restaurant industry. *International Journal of Hospitality Management*, *71*, 19–32. https://doi.org/10.1016/j.ijhm.2017.09.004

Graham, M. E., & Bansal, P. (2007). Consumers' Willingness to Pay for Corporate Reputation: The Context of Airline Companies. *Corporate Reputation Review*, *10*(3), 189–200. https://doi.org/10.1057/palgrave.crr.1550052

Guyon, I., Weston, J., Barnhill, S., & Vapnik, V. (2002). Gene selection for cancer classification using support vector machines. *Machine Learning*, *46*, 389–422. https://doi.org/10.1023/A:1012487302797

Halpern, N., & Mwesiumo, D. (2021). Airport service quality and passenger satisfaction: The impact of service failure on the likelihood of promoting an airport online. *Research in Transportation Business and Management*, *41*. https://doi.org/10.1016/j.rtbm.2021.100667

He, R. R., Chen, Y., Huang, Q., & Kang, Y. (2019). LASSO as a tool for downscaling summer rainfall over the Yangtze River Valley. *Hydrological Sciences Journal*, *64*(1), 92–104. https://doi.org/10.1080/02626667.2019.1570210

Hu, F., & Trivedi, R. H. (2020). Mapping hotel brand positioning and competitive landscapes by text-mining user-generated content. *International Journal of Hospitality Management*, *84*, 102317. https://doi.org/10.1016/j.ijhm.2019.102317

Hussain, R., Al Nasser, A., & Hussain, Y. K. (2015). Service quality and customer satisfaction of a UAE-based airline: An empirical investigation. *Journal of Air Transport Management*, *42*, 167–175. https://doi.org/10.1016/j.jairtraman.2014.10.001

ICAO. (2017). *The World of Air Transport in 2017*. https://www.icao.int/annual-report-2017/Pages/the-world-of-air-transport-in-2017.aspx

Idris, F., & Naqshbandi, M. M. (2019). Exploring competitive priorities in the service sector: evidence from India. *International Journal of Quality and Service Sciences*, *11*(2), 167–186. https://doi.org/10.1108/IJQSS-02-2018-0021

Jandaghi, G., Saranj, A., Rajaei, R., Ghasemi, A., & Tehrani, R. (2021). Identification of the Most Critical Factors in Bankruptcy Prediction and Credit Classification of Companies. *Iranian Journal of Management Studies*, *14*(4), 817–834. https://doi.org/10.22059/IJMS.2021.285398.673712

Jeeradist, T., Thawesaengskulthai, N., & Sangsuwan, T. (2016). Using TRIZ to enhance passengers' perceptions of an airline's image through service quality and safety. *Journal of Air Transport Management*, *53*, 131–139. https://doi.org/10.1016/j.jairtraman.2016.02.011

Jeng, S. P., & Lo, M. F. (2019). Lowest price guarantees on airline websites: Perceived believability, perceived value, and purchase intentions. *Journal of Air Transport Management*, *75*, 85–91. https://doi.org/10.1016/j.jairtraman.2018.12.002

Kaura, V., Prasad, C. S. D., & Sharma, S. (2015). Service quality, service convenience, price and fairness, customer loyalty, and the mediating role of customer satisfaction. *International Journal of Bank Marketing*, *33*(4), 404–422. https://doi.org/10.1108/IJBM-04-2014-0048

Kayapınar, S., & Erginel, N. (2019). Designing the airport service with fuzzy QFD based on SERVQUAL integrated with a fuzzy multi-objective decision model. *Total Quality Management and Business Excellence*, *30*(13–14), 1429–1448. https://doi.org/10.1080/14783363.2017.1371586

Koklic, M. K., Kukar-Kinney, M., & Vegelj, S. (2017). An investigation of customer satisfaction with low-cost and full-service airline companies. *Journal of Business Research*, *80*(C), 188–196. https://doi.org/10.1016/j.jbusres.2017.05.015

Lee, C. Y., & Cai, J. Y. (2020). LASSO variable selection in data envelopment analysis with small datasets. *Omega (United Kingdom)*, *91*, 102019. https://doi.org/10.1016/j.omega.2018.12.008

Littman, M. L., & Turney, P. D. (2003). Measuring Praise and Criticism: Inference of Semantic Orientation from Association. *ACM Transactions on Information Systems*, *21*(4), 315–346.

Lucini, F. R., Tonetto, L. M., Fogliatto, F. S., & Anzanello, M. J. (2020). Text mining approach to explore dimensions of airline customer satisfaction using online customer reviews. *Journal of Air Transport Management*, Epub ahead of print 27 December 2019. https://doi.org/10.1016/j.jairtraman.2019.101760

Manuela, W. S., Rhoades, D. L., & Curtis, T. (2019). Market power at the Seattle-Tacoma International Airport: The case of Alaska Airlines. *Transport Policy*, *76*, 90–99. https://doi.org/10.1016/j.tranpol.2018.12.013

Messner, W. (2020). The impact of language proficiency on airline service satisfaction. *Journal of Travel and Tourism Marketing*, *37*(2), 169–184. https://doi.org/10.1080/10548408.2020.1740139

Mirzaei, A., Pourahmadi, V., Soltani, M., & Sheikhzadeh, H. (2020). Deep feature selection using a teacher-student network. *Neurocomputing*, *383*, 396–408. https://doi.org/10.1016/j.neucom.2019.12.017

Nielsen. (2014). *Indonesian Consumers Flock Online to Purchase Products and Service*. https://www.nielsen.com/id/en/press-releases/2014/indonesian-consumers-flock-online-to-purchase-products-and-services/

O'Connell, J. F., Avellana, R. M., Warnock-Smith, D., & Efthymiou, M. (2020). Evaluating drivers of profitability for airlines in Latin America: A case study of Copa Airlines. *Journal of Air Transport Management*. https://doi.org/10.1016/j.jairtraman.2019.101727

Oliveira, D. S. de, & Caetano, M. (2019). Market strategy development and innovation to strengthen consumer-based equity: The case of Brazilian airlines. *Journal of Air Transport Management*, *75*, 103–110. https://doi.org/10.1016/j.jairtraman.2018.12.006

Parasuraman, a, Zeithaml, V. a, & Berry, L. L. (1988). SERQUAL: A Multiple-Item scale for Measuring Consumer Perceptions of Service Quality. *Journal of Retailing*, *64*, 12–40. https://doi.org/10.1016/S0148-2963(99)00084-3

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A Conceptual Model of Service Quality and Its Implications for Future Research. *Journal of Marketing*, *49*(4), 41–50. https://doi.org/10.2307/1251430

Park, J. W., Robertson, R., & Wu, C. L. (2004). The effect of airline service quality on passengers' behavioural intentions: A Korean case study. *Journal of Air Transport Management*, *10*(6), 435–439. https://doi.org/10.1016/j.jairtraman.2004.06.001

Parzinger, M., Hanfstaengl, L., Sigg, F., Spindler, U., Wellisch, U., & Wirnsberger, M. (2022). Comparison of different training data sets from simulation and experimental measurement with artificial users for occupancy detection — Using machine learning methods Random Forest and LASSO. *Building and Environment, 223*. https://doi.org/10.1016/j.buildenv.2022.109313

Peitzika, E., Chatzi, S., & Kissa, D. (2020). Service Quality Expectations in the Fitness Center Context: A Validation of the Expectations Component of the SERVQUAL Scale in Greece. *Services Marketing Quarterly*, *41*(2), 89–104. https://doi.org/10.1080/15332969.2020.1742977

Perçin, S. (2018). Evaluating airline service quality using a combined fuzzy decision-making approach. *Journal of Air Transport Management*, *68*, 48–60. https://doi.org/10.1016/j.jairtraman.2017.07.004

Rajaguru, R. (2016). Role of value for money and service quality on behavioural intention: A study of full service and low cost airlines. *Journal of Air Transport Management*, *53*, 114–122. https://doi.org/10.1016/j.jairtraman.2016.02.008

Reimers, I., & Xie, C. C. (2019). Do coupons expand or cannibalize revenue? evidence from an e-market. *Management Science*, *65*(1), 1–15. https://doi.org/10.1287/mnsc.2017.2934

Sahran, S., Albashish, D., Abdullah, A., Shukor, N. A., & Hayati Md Pauzi, S. (2018). Absolute cosine-based SVM-RFE feature selection method for prostate histopathological grading. *Artificial Intelligence in Medicine*, *87*, 78–90. https://doi.org/10.1016/j.artmed.2018.04.002

Sezgen, E., Mason, K. J., & Mayer, R. (2019). Voice of airline passenger: A text mining approach to understand customer satisfaction. *Journal of Air Transport Management*, *77*, 65–74. https://doi.org/10.1016/j.jairtraman.2019.04.001

Shah, F. T., Syed, Z., Imam, A., & Raza, A. (2020). The impact of airline service quality on passengers' behavioral intentions using passenger satisfaction as a mediator. *Journal of Air Transport Management*, *85*, 101815. https://doi.org/10.1016/j.jairtraman.2020.101815

Shao, Z., Yang, S. L., Gao, F., Zhou, K. Le, & Lin, P. (2017). A new electricity price prediction strategy using mutual information-based SVM-RFE classification. *Renewable and Sustainable Energy Reviews*, *70*, 330–341. https://doi.org/10.1016/j.rser.2016.11.155

Shieh, M. D., & Yang, C. C. (2008). Multiclass SVM-RFE for product form feature selection. *Expert Systems with Applications*, *35*(1–2), 531–541. https://doi.org/10.1016/j.eswa.2007.07.043

Siering, M., Deokar, A. V, & Janze, C. (2018). Disentangling consumer recommendations: Explaining and predicting airline recommendations based on online reviews. *Decision Support Systems*, *107*, 52–63. https://doi.org/10.1016/j.dss.2018.01.002

Song, C., Guo, J., & Zhuang, J. (2020). Analyzing passengers' emotions following flight delays- a 2011–2019 case study on SKYTRAX comments. *Journal of Air Transport Management*. https://doi.org/10.1016/j.jairtraman.2020.101903

Srikanta Patnaik, S., Tajeddini, K., & Jain, V., . (2021). Computational management: Applications of computational intelligence in business management. Switzerland: Modeling and Optimization in Science and Technologies : Springer.

Tajeddini, K. (2011). The effects of innovativeness on effectiveness and efficiency. *Education, Business and Society: Contemporary Middle Eastern Issues*, *4*(1), 6–18. https://doi.org/10.1108/17537981111111238

Tansitpong, P. (2020). Determinants of Recommendation in the Airline Industry: An Application of Online Review Analysis. *Lecture Notes in Business Information Processing*, *384 LNBIP*, 125–135. https://doi.org/10.1007/978-3-030-46224-6_10

Tarkang, M. M. E. M., Alola, U. V., Nange, R. Y., & Ozturen, A. (2020). Investigating the factors that trigger airline industry purchase intention. *Current Psychology*. https://doi.org/10.1007/s12144-020-00815-z

Tibshirani, R. (1996). Regression Shrinkage and Selection Via the Lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Tommasel, A., & Godoy, D. (2018). A Social-aware online short-text feature selection technique for social media. *Information Fusion*, *40*, 1–17. https://doi.org/10.1016/j.inffus.2017.05.003

Trivedi, S. K., Dey, S., & Kumar, A. (2018). Capturing user sentiments for online Indian movie reviews. *The Electronic Library*, *36*(4), 677–695. https://doi.org/10.1108/el-04-2017-0075

Vlachos, I., & Lin, Z. (2014). Drivers of airline loyalty: Evidence from the business travelers in China. *Transportation Research Part E: Logistics and Transportation Review*, *71*, 1–17. https://doi.org/10.1016/j.tre.2014.07.011

Wahyuni TD, I. S., & Fernando, Y. (2016). Growing pains the low cost carrier sector in Indonesia: Internal service quality using a critical incident technique. *Safety Science*, *87*, 214–223. https://doi.org/10.1016/j.ssci.2016.04.003

Wang, R., Li, W., Li, R., & Zhang, L. (2019). Automatic blur type classification via ensemble SVM. *Signal Processing: Image Communication*, *71*, 24–35. https://doi.org/10.1016/j.image.2018.08.003

Wu, W., & Riantama, D. (2022). Determining the factors affecting customer satisfaction using an extraction-based feature selection approach. *PeerJ Computer Science*, *8*, e850. https://doi.org/10.7717/peerj-cs.850

Yi, Y., & Yoo, J. (2011). The long-term effects of sales promotions on brand attitude across monetary and non-monetary promotions. *Psychology and Marketing*, *37*(2), 197–206. https://doi.org/10.1002/mar.20416

Zhang, C. H., & Huang, J. (2008). The sparsity and bias of the lasso selection in high-dimensional linear regression. *Annals of Statistics*, *36*(4), 1567–1594. https://doi.org/10.1214/07-AOS520

Zhang, S., & Duan, X. (2018). Prediction of protein subcellular localization with oversampling approach and Chou's general PseAAC. *Journal of Theoretical Biology*, *437*, 239–250. https://doi.org/10.1016/j.jtbi.2017.10.030

Zhao, D., Liu, H., Zheng, Y., He, Y., Lu, D., & Lyu, C. (2019). A reliable method for colorectal cancer prediction based on feature selection and support vector machine. *Medical and Biological Engineering and Computing*, *57*(4), 901–912. https://doi.org/10.1007/s11517-018-1930-0

Zhao, P., & Yu, B. (2006). On model selection consistency of Lasso. *Journal of Machine Learning Research*, *7*(12), 2541–2563.

Zheng, W., Zhu, X., Wen, G., Zhu, Y., Yu, H., & Gan, J. (2020). Unsupervised feature selection by self-paced learning regularization. *Pattern Recognition Letters*, *132*, 4–11. https://doi.org/10.1016/j.patrec.2018.06.029