Performance Analysis for Passenger Satisfaction of Kuala Lumpur International Airport

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Abstract. Kuala Lumpur International Airport (KLIA) serves as the country's primary international gateway, providing the first impression to airport users and visitors. It also provides incomparable benefits to Malaysia's economy, such as tourism. Therefore, the airport requires to focus on the passenger's experience and satisfaction to deliver better service and meet their expectations. The objectives were to determine the association between the service quality of the airport and KLIA passenger's recommendation by Chi-square test, the passenger's recommendation based on the airport services quality by logistic regression, and the KLIA passenger's satisfaction and experience through the passenger's online review to be investigated by text mining technique, word cloud and sentiment analysis. The data used in this study were collected from August 2015 to February 2021 through the Skytrax website. The results showed an association between the eight distinct types of service quality of airports and passenger recommendations in KLIA by using the Chi-square test. Bayesian Information Criterion shows that the six variables model were significant to the KLIA passenger recommendation to another passenger whether it is a satisfying airport. Moreover, the term "staff" was the most frequently occurring word among the passenger reviews by using text mining techniques. Based on the sentiment analysis, the passenger reviews were more likely to be the neutral sentiment. Hence, it is recommended to place a smiley box in each toilet and ask people to rate the cleanliness of that specific toilet rather than the entire restroom, as it increases practical usability by reducing the number of contradictories votes each time interval.

Keywords: Kuala Lumpur International Airport · Logistic Regression · Text Mining Technique · Sentiment Analysis

1 Introduction

An airport, also known as an aerodrome or an airfield, was defined as a place that consisted of runways and buildings for the aircraft's take-off and landing from one location to another domestically or internationally. Besides, the airport provides aircraft maintenance facilities as well as passenger and cargo terminal services. Malaysia is a Southeast Asian country with eight international airports, and KLIA serves as the country's primary international gateway. The KLIA's location is Sepang, District of Selangor, and it

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started operating on 27 June 1998 under Mahathir Mohamad's government. The KLIA is operated by Malaysia Airports Holdings Berhad (MAHB). Kisho Kurokawa, a Japanese Architect, designed it. The airport in harmony with nature, tradition and innovative technologies is KLIA's design concept [1].

East and West Air Traffic Control (ATC) Tower is located at the KLIA to monitor the runways, and the ATC Tower West is the world's tallest ATC Tower. KLIA consists of two terminals known as KLIA and KLIA 2. On 2 May 2014, KLIA 2 was officially started operations, and it was the largest low-cost carrier terminal worldwide with a site that spans 100 squares kilometres of former agricultural land, which can manage 70 million passengers per year. KLIA provides many incomparable benefits to Malaysia's economy, such as tourism. For the tourism sector, the increase of visitors and airport users mention the local economy with the inflow of money. It managed 62,336,469 passengers and ranked as the 21 busiest airports in terms of passenger traffic worldwide [2]. Besides that, KLIA provided a cargo service that transported 714,669 tons of cargo volume in 2018, which provides local businesses opportunities to export their product to the global market.

The airport's service quality performance may influence customer satisfaction and expectations. The continuous improvement of service quality allows the airport to meet customer demands while also improving its reputation. Improving customer satisfaction by defining and exceeding their desires and aspirations can help in expanding airport sales and engaging patronage with customers [3]. This was because KLIA provided the first impression to airport users and visitors. When they arrive at their destination, the tourist's first point of contact is the airport, and its infrastructure and facilities will give them their first impression of the expected quality of their vacation time [4]. Activities passenger's outbound shopping was one of the most favourite activities to meet the tourist desire for fun and relaxation [5, 6]. However, the airport's services quality needed improvement to meet the passenger's expectations and satisfaction. Moreover, airport security was also one of the factors that might affect customer satisfaction. The most crucial criterion for evaluating airport service was the security check [7]. The airport's service quality needs to be improved because everyone expects high-quality service in the age of technology. The airport's manager should understand passengers' expectations and need to deliver a better service [8].

In conjunction with that, KLIA needs to survive by knowing each airport user and visitor's service quality expectations and competing with other international airports. Therefore, this study determined the association between airport services quality and the passenger's recommendation, predicted the passenger's recommendation based on the airport services quality and identified KLIA passenger's experience based on online reviews. The Skytrax website was used to collect the data set from August 2015 until February 2021, and it consisted of passenger reviews and airport services ratings.

2 Methodology

2.1 Data Description

Skytrax was a global air transport rating organisation that included an email verification system, allowing the passengers to include their email addresses to validate their

Table 1. List of variables

Variable	Description	Level of variable
Country	Respondent's country	Nominal
Experience at Airport	1 = Arrival, 2 = Departure, 3 = Arrival and Departure, 4 = Transit	Nominal
Types of Travelers	1 = Solo Leisure, 2 = Couple Leisure, 3 = Family Leisure, 4 = Business	Nominal
Queuing Time	1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied 5 = Very satisfied	Ordinal
Terminal Cleanliness		
Terminal Seating		
Terminal Signs		
Food Beverage		
Airport Shopping		
WIFI Connectivity		
Airport Staff		
Recommend	1 = Recommend, 0 = Not Recommend	Nominal
Review	The customer and passenger overall experience and satisfaction in the airport	Text

reviews and reflect their desire to deliver their airport experiences [9]. There were 287 data collected from the website, including the passenger's country, experience at the airport and types of travellers. The experience at the airport and types of travellers, both variables consisted of four different descriptions. The dataset also included queuing time, terminal cleanliness, terminal seating, terminal signs, food beverages, airport shopping, WIFI connectivity, and airport staff as service quality and passenger reviews based on their satisfaction in the airport. This research focused primarily on passengers' satisfaction based on the airport services performance. Table 1 displays the variable with their description and the level of the variable.

2.2 Chi-Square Test for Independence

Chi-square statistic was a non-parametric and a test of statistical significance performed on categorical data with several assumptions such as frequencies or count in the data cell. The level of variables should be mutually exclusive, every subject may contribute data to one and only one cell in $X2$, the study groups must not be dependent, there were two variables with both categorical variables and the cell expected value should be at least 5 in at least 80% of the cell.

The expected value for the Chi-square test is as follows

$$E_i = \frac{M_R x M_C}{N} \tag{1}$$

where E_i represented the expected value, M_R represented the row marginal for that cell, M_C represented the column marginal for the cell, and N represented the total sample size.

The Chi-square test is

$$X^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{2}$$

where O_i represented the observed value, E_i represented the expected value, X^2 represented the cell chi-square value.

H_0: There is no association between the two variables.

H_1: There is an association between two variables.

The null hypothesis will be rejected if the p-value is less than a 5% significance level, and it can be concluded that there is an association between the two variables. Otherwise, the null hypothesis will be accepted.

2.3 Logistic Regression

Binary logistic regression was commonly used when the explanatory variable was continuous or categorical, and the response variable was dichotomous. An ordinal data set was used as the independent variable in this research and coded numerically depending on each passenger's satisfaction with each variable. It was processed in R-studio statistical program for further analysis. This study included multiple independent variables and one dependent variable. The passenger's recommendations of KLIA to other passengers on whether KLIA is a satisfied airport as the dependent variable, with one representing recommended airport and zero representing not recommended airport.

The ratio of the probability that an event will occur to the probability that it will not occur was defined as the event's odds. By using the natural logarithm to transform the odds, the natural log odds as a linear function of the explanatory variable [10] were expressed as

$$logit(y) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k \tag{3}$$

where p represented the probability of the event occurring while (1-p) was the probability of the event not occurring, β_o was the intercept term while $\beta_1, \ldots, \beta_k$ was the estimated coefficient for the k explanatory variables $X_1, \ldots, X_k$. The prediction of the probability of the occurrence of the interesting outcome as

$$p = \frac{e^{\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k}}{1 + e^{\beta_0 + \beta_1 \beta_1 + \cdots + \beta_k \beta_k}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \beta_1 + \cdots + \beta_k \beta_k)}} \tag{4}$$

where the predicted probability must be bounded between zero and one, a low probability indicated a high odd ratio [10]. The odds ratio can range from zero to infinity, and it measured the effect of independent variables on the likelihood of the outcome.

2.4 Text Mining Technique

Text mining was a subset of data mining that sought interesting trends and extracted valuable knowledge from various databases [11]. It sought trends in unstructured data such as memos, notes, pdf, and text files [12]. The text mining process started with data collecting, followed by the data cleaning process. Data cleaning was the procedure that removed abnormality, missing and duplicate data from the massive data sources. Next, the text data was gone through a text analysis phase: text frequency. The text mining technique determined the word frequency appearing in the customer reviews.

Other than that, the correlation words that found by using the find associations function through R-studio statistical software. The scores range from 0 to 1. A score of 1 means that two words always appear together in documents, while a score approaching 0 means the terms seldom appear in the same document. The result shows all the correlation words have the strength of at least 0.3 to the specific words. The correlation words provide a clear understanding of the link word to the airport management for the top ten frequent words.

2.5 Word Cloud

Word cloud was known as a tag cloud that may analyse text data such as essays or short answers to surveys or opinion questions [13]. A word cloud was used to visualise text data or language, and it was a significant subfield of data mining that has grown in popularity and application opportunities in Big Data time [14]. A word cloud was a visual representation of information that enables a reader to form an intuitive understanding of a document quickly, and it was a straightforward way to deliver high-level data without overwhelming the user [13]. The font size in the word cloud denoted the frequency. The more frequently a term appears in the dataset, the greater the font size [15]. The word cloud process began with retrieving data from the Skytrax website that contains the KLIA passenger review. Next, different packages were installed before applying text mining techniques, followed by the document-term matrix. The table containing the word's frequency was a document matrix, where the columns represented words while the rows represented documents. The review of the passenger of KLIA was in text form. Therefore, the passenger's review generated a word cloud in this study.

2.6 Sentiment Analysis

Sentiment analysis was a statistical technique that identifies whether a piece of text is negative, neutral, or positive [16]. It used characteristics to identify a customer's opinion or feeling towards a brand. Therefore, sentiment analysis was applied to analyse and assess customer satisfaction based on the passenger reviews of KLIA. The initial step of sentiment analysis was the text pre-processing with tokenisation and normalisation. Tokenisation converted text into tokens before transforming it into vectors. After tokenisation, stop words were filtered. Stop words were the most often appearing words irrelevant in the data context and provided no deeper meaning to the phrase. Following that, normalisation entailed casing the character and negation handling. Lemmatisation was a technique for extracting the base form of the words by removing inflexion in words

[17]. Lastly, the sentiment scores were determined based on the review provided by the passengers.

There are three different sentiment analyses *syuzhet*, *bing*, and *afinn* methods. There three sentiment analyses were all those lexicons that can be retrieved within the *syuzhet* package through a function that reports their sentiment score by using *R-studio*. The sentiment score obtained with the calculation of the number of negative words are subtracted from the number of positive words and divided by the total words.

3 Result and Discussion

The data analysis conducted on passengers' satisfaction at KLIA was presented in this section and the results were tabulated in tables, figures and accompanied by their respective interpretations.

3.1 Chi-Square Test

The chi-square test determined whether there is an association or no association between eight types of airport service attributes independent variables and one dependent variable. The eight distinct airport service attributes included queuing time, terminal cleanliness, terminal seating, food beverage, airport shopping, WIFI connectivity, and airport staff. The dependent variable was the passenger's recommendations of KLIA to other passengers regarding whether KLIA is a satisfied airport.

Table 2 displays the chi-square test results between eight types of airport service quality and the passenger's recommendations of KLIA to other passengers regarding whether KLIA is a satisfied airport. The *p*-value between all independent and dependent variables were 0.000, which shows significant variables. Since the *p*-value was less than 0.05 significance level, it can be concluded that there was an association between eight types of airport service attributes and the passenger's recommendations of KLIA to other passengers regarding where KLIA was a satisfied airport. The total percentage of satisfied and very satisfied passengers for eight distinct types of airport service quality is also shown in Table 2. The airport staff service quality had the lowest percentage of passengers who voted satisfied or very satisfied among all airports' service quality with only 29.84%, but 49 of the 57 passengers recommended KLIA as a satisfied airport to other passengers. This concluded that most of the passengers who were satisfied and very satisfied with the airport staff also recommend KLIA as the satisfying airport to other passengers.

3.2 Logistic Regression Model

From the start of the model building process, the data was divided into training and testing set in proportions of 90% and 10%. Since the data were categorical variables, no elimination strategy was utilised to create the logistic regression model. Table 3 shows the coefficients and *p*-value for variables.

Few independent variables were positively related to the dependent variable, such as Queuing Time-2, Queuing Time-4, Queueing Time-5, Terminal Cleanliness-2, Terminal Cleanliness-3, Terminal Cleanliness-4, Terminal Cleanliness-5, Terminal Seating-2,

Table 2. Chi-square test of customer satisfaction on airport service quality

Airport service quality	Chi-square test	p-value	Decision	Satisfied and very satisfied	Recommendation
Queuing time	77.252	0.000	Reject H_0	68 (35.60%)	52 (76.47%)
Terminal cleanliness	92.68	0.000	Reject H_0	79 (41.37%)	59 (74.68%)
Terminal seating	68.322	0.000	Reject H_0	58 (30.37%)	45 (77.59%)
Terminal signs	74.634	0.000	Reject H_0	85 (44.50%)	58 (68.24%)
Food beverage	68.397	0.000	Reject H_0	72 (37.70%)	50 (69.44%)
Airport shopping	75.02	0.000	Reject H_0	73 (38.22%)	55 (75.34%)
WIFI connectivity	58.858	0.000	Reject H_0	82 (42.93%)	54 (65.85%)
Airport staff	97.997	0.000	Reject H_0	57 (29.84%)	49 (85.96%)

Table 3. Coefficients and p-value for variables

Variable	Coef.	p-value	Variable	Coef.	p-value
Intercept	−181.0956	0.9921			
Queuing Time 2	0.5361	0.8412	Food Beverages 2	6.7529	0.4093
Queuing Time 3	−1.3906	0.3709	Food Beverages 3	7.8332	0.3420
Queuing Time 4	6.1827	0.0530	Food Beverages 4	10.1688	0.2658
Queuing Time 5	40.6291	0.9941	Food Beverages 5	38.0150	0.9948
Terminal Cleanliness 2	3.5252	0.0896	Airport Shopping 2	−2.5684	0.7383
Terminal Cleanliness 3	0.4307	0.8509	Airport Shopping 3	−6.0744	0.4314
Terminal Cleanliness 4	0.8212	0.6574	Airport Shopping 4	−1.3196	0.8651
Terminal Cleanliness 5	44.8820	0.9920	Airport Shopping 5	−9.7964	0.3287
Terminal Seating 2	1.1182	0.5453	WIFI Connectivity 2	26.7300	0.9982
Terminal Seating 3	4.7552	0.1052	WIFI Connectivity 3	27.5662	0.9981
Terminal Seating 4	4.7011	0.1818	WIFI Connectivity 4	24.5736	0.9983
Terminal Seating 5	−43.4436	0.9922	WIFI Connectivity 5	16.6494	0.9988
Terminal Signs 2	142.5670	0.9919	Airport Staff 2	7.0577	**0.0369**
Terminal Signs 3	141.5670	0.9919	Airport Staff 3	5.5408	**0.0278**
Terminal Signs 4	138.0919	0.9921	Airport Staff 4	9.7797	**0.0452**
Terminal Signs 5	145.6604	0.9917	Airport Staff 5	37.4085	0.9903

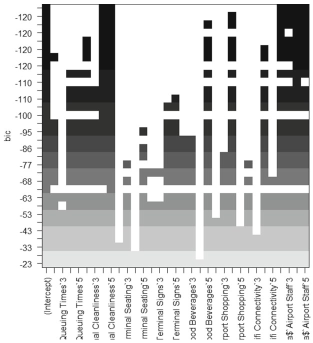

Fig. 1. Bayesian Information Criterion (BIC) of the regression model

Terminal Seating-3, Terminal Seating-4, Terminal Signs-2, Terminal Signs-3, Terminal Signs-4, Terminal Signs-5, Food Beverage-2, Food Beverage-3, Food Beverage-4, Food Beverage-5, WIFI Connectivity-2, WIFI Connectivity-3, WIFI Connectivity-4, WIFI Connectivity-5, Airport Staff-2, Airport Staff-3, Airport Staff-4 and Airport Staff-5. This meant that if the passengers at KLIA the variables mentioned above, it would increase the possibility of having a positive recommendation, where the coefficient represented the possibility. For example, if the customers selected Queuing Time-5, there was 40.63% to have a favourable recommendation. Other than that, few independent variables were negatively related to the dependent variable, such as Queuing Time-3, Terminal Seating-5, Airport Shopping-2, Airport Shopping-3, Airport Shopping-4, and Airport Shopping-5. If one of the passengers at KLIA rated the variables mentioned above, it would decrease the possibility of having a positive recommendation, where the coefficient represented the possibility. For instance, if the customers selected Queuing Time-3, there was 1.39% to have a negative recommendation. Moreover, most of the *p*-values in Table 3 were more than 0.05, indicating that the variables were not significant. Three variables bold in Table 3 were found to be significant such as airport staff 2, airport staff 3, and airport staff 4.

Figure 1 shows the BIC of the regression model. Each plot's top row comprised a black square for each variable chosen based on the best model for that statistic. For example, numerous models had a BIC close to -120. However, the six-variable model with the lowest BIC included terminal cleanliness-4, terminal cleanliness-5, airport staff-2, airport staff-3, airport staff-4, and airport staff-5. Hence the six variables model were significant to the KLIA passenger recommendation to another passenger whether it is a satisfying airport. The airport staff's courtesy was more important to frequent flyers [18], whereas ICQ, mobility, convenience, and security were essential for infrequent users. Therefore, airport management should educate airport staff on the significance of their customer service attitudes [18].

3.3 Text Mining Techniques

The *R-studio* statistical software was used for the text mining technique in this study. It was implemented to discover the unstructured online reviews by the airport passenger

Fig. 2. Word cloud of airport passenger review at KLIA

into valuable information. This sub-chapter provides keywords frequency and a word cloud to recognise reviews from a passenger from KLIA.

The top 30 most often used words in reviews from the passengers at KLIA are listed in Table 4. As a result, the passenger evaluation's top three most frequently occurring words were "staff", "immigration", and "gate", which appeared 141 times, 125 times, and 97 times, respectively. As a result, some terms describing airport staff and services, such as "immigration", "security", "counter", and "check", frequently appear in passenger reviews. Additionally, the terms "queue", "clean", "long", and "wait" were included in their comment on their airport passenger evaluation at KLIA. The frequent use of "hour" and "wait" in airport-related words suggested that people who were concerned about airports were also concerned about the airport waiting process [19].

Figure 2 depicts the total frequency distribution of essential words that appeared most frequently in reviews from passengers at KLIA and the words that appeared at least ten times in the airport passenger reviews. The font size indicated the importance of the text. Since the term "staff" appeared most frequently in passenger reviews, its size was the largest compared to the other terms in the figure.

The top ten most frequently used words in airport passenger reviews at KLIA are shown in Table 5. The term "staff" was the most frequently mentioned word in airport passenger reviews at KLIA. The correlation words for staff were "volunteer" and "everywhere", implying that there were several staff members working in the airport and volunteering to assist travellers who encountered difficulties.

Apart from that, the terms "line", "hour", and "queue" all refer to "immigration". This demonstrated that the line-up for the immigration sector was perpetually long, causing travellers to spend an hour passing through the part. Next, the terms "employ", "security", "board", and "entire" referred to the "gate". These few terms indicated that the KLIA expends considerable work on onboarding gates to improve the boarding process while maintaining the entire airport's security.

Apart from that, "normal" and "peak" indicated the regular and peak hours at KLIA, respectively, relating to the term "time". The terms "queue" and "check" in the top ten most frequently used words both had the same correlation words, which were "discard" and "elevator," indicating that the management of KLIA wished to discard the queue by

Table 4. Top 30 frequent words from airport passenger review at KLIA

Rank	Word	Freq.	Rank	Word	Freq.	Rank	Word	Freq.
1	Staff	141	11	Terminal	70	21	Counter	46
2	Immigration	125	12	Arrive	63	22	Take	45
3	Gate	97	13	People	55	23	Transit	45
4	Time	92	14	Clean	54	24	Departure	43
5	Check	92	15	Board	50	25	Help	42
6	Flight	90	16	Long	50	26	Seat	40
7	Security	82	17	Hour	49	27	Service	40
8	Toilet	76	18	Area	48	28	Line	39
9	Queue	72	19	Shop	47	29	Place	39
10	Passenger	71	20	Wait	46	30	Good	37

Table 5. Correlations between the most frequently occurring words

Words	Correlations words
Staff	Volunteer (0.32), everywhere (0.30)
Immigration	Line (0.38), hour (0.37), queue (0.32)
Gate	Employ (0.44), security (0.43), board (0.37), entire (0.30)
Time	Normal (0.34), peak (0.34)
Check	Discard (0.50) elevator (0.5)
Flight	Announce (0.46), miss (0.37), schedule (0.36), display (0.36)
Security	Checkpoint (0.46), drink (0.4), plastic (0.40), throw (0.38)
Toilet	Wet (0.59), female (0.54)
Queue	Discard (0.50) elevator (0.5)
Passenger	Display (0.44), faster (0.38), flight (0.33), gate (0.32), schedule (0.32)

using the elevator after checking the travellers' passports and tickets, to save time and minimise the possibility of a long queue.

3.4 Sentiment Analysis

Sentiment analysis determined the passenger's emotions at KLIA through reviews. Sentiments were classified as positive, negative, or neutral. They were also expressed numerically to more accurately convey the positivity or negativity degree included within a piece of text. Table 6 shows the summary of three different sentiment analyses.

The value of -1 indicated the most negative, and $+1$ indicated the most positive when using the *syuzhet* or *bing* method. The scale for sentiment scores using the *afinn*

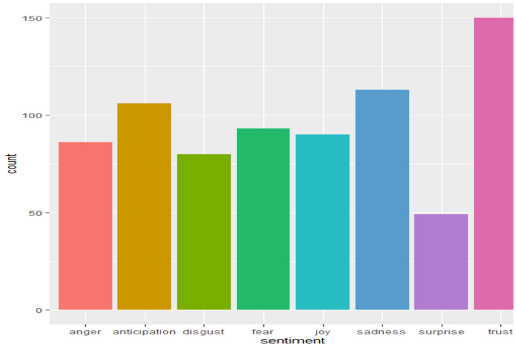

Fig. 3. Passenger review sentiment score

Table 6. The summary of three different sentiment analysis methods

Words	Summary (*syuzhet_vector*)	Summary (*bing_vector*)	Summary (*afinn_vector*)
Min	−6.3500	−12.0000	−16.0000
1^{st} Qu	−1.1250	−2.0000	−5.0000
Median	0.7000	0.0000	0.0000
Mean	0.9686	0.2408	0.4921
3^{rd} Qu	2.9250	3.0000	6.0000
Max	11.2000	15.0000	26.0000

method was decimal and ranged from −5 to +5. The value of −5 showed the most negative, and +5 indicated the most positive. The overall average sentiment across all the responses was positive using the *syuzhet* vector since the summary statistics showed a median value of 0.7 above zero. Moreover, the overall average sentiment across all the responses was neutral when using *bing* and *afinn* vectors since the summary statistics showed the median value of sentiment scores were zero.

The *get_nrc_sentiments* method displayed the passenger's feelings for the KLIA in Fig. 3. The NRC Emotion Lexicon lists English words and their associations with eight basic emotions: anger, fear, anticipation, trust, surprise, sadness, joy, and disgust. In the passenger review on the Skytrax website, terms connected with the "trust" positive emotion appeared 150 times, whereas words related to the "disgust" negative emotion appeared lower than 80 times. The lowest emotion count among eight distinct types of emotion was "surprised" at 49 times based on passenger reviews. A better picture of the overall feeling in the passenger review was obtained by comparing these numbers as a percentage of the total number of meaningful words. The emotion in the passenger's review is depicted in Fig. 4. The "trust" emotion had the longest bar whereas, the "surprise" emotion had the shortest bar. Both emotions indicate that the terms associated with the positive emotion constitute just over 19.56% and 7% of all the meaningful words in this text, respectively. The total percentage of positive sentiment was 37.68%, including

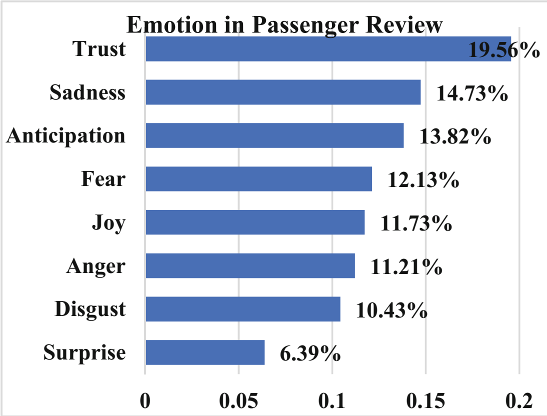

Fig. 4. Emotion in passenger review

trust, joy, and surprise, whereas negative sentiment was 48.5%, including sadness, fear, anger, and disgust. Based on all sentiment analyses, it was concluded that the KLIA passengers' review was more likely to be the neutral sentiment.

4 Conclusion

In conclusion, all three objectives were successfully achieved. There was an association between the eight distinct airport service quality and passenger recommendations in the KLIA. Terminal cleanliness-4, terminal cleanliness-5, airport staff-2, airport staff-3, airport staff-4, airport staff-5 were the variables that were significant to the KLIA passenger recommendations to other passengers whether it is a satisfying airport. In the passenger reviews from KLIA, the total percentage of positive sentiment and negative sentiment were the same and concluded that the reviews were more likely to be neutral sentiment. Numerous studies have used passenger happiness as a proxy for an organisation's service improvement. Several constraints were encountered in this research, including passenger satisfaction was measured using eight distinct service qualities. As a result, additional service quality such as accommodation and public transport services can be included in a subsequent research study focusing on various areas to produce a more valuable conclusion. Moreover, each traveller will have a satisfaction level. For example, one individual may visit a clean toilet in the same restroom while another visits a dirty toilet, resulting in two contradictory votes. A solution would be to place a smiley box in each toilet and ask people to rate the cleanliness of that specific toilet rather than the entire restroom as it increases practical usability by reducing the number of contradictories votes each time interval [20].

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Authors' Contributions. The outcomes in this study are helpful for the relevant government agencies and airport managers to understand the demands of airport users and can influence strategic planning and policy formation to support long-term efficiency, thus resulting in better service delivery.

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