Unveiling perceptions: aspect-based sentiment analysis of Malaysia's e-hailing reviews

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ABSTRACT

The growing demand for e-hailing services in Malaysia leads to increased competition among more than 20 licensed e-hailing service providers. Consumer satisfaction is a crucial factor influencing variables in the business organization, and understanding consumers' perceptions is vital for service improvement. Reviews on e-hailing services are unstructured data and massive, making comparisons difficult. Thus, this study aims to classify Malaysia's e-hailing service reviews from Google Play Store and X using latent Dirichlet allocation (LDA) and support vector machine (SVM). Aspect-based sentiment analysis (ABSA) was performed using a two-staged method, applying LDA for aspect category detection and SVM for aspect sentiment classification separately. Fare, availability, comfort, time, and convenience are five predetermined aspect categories in this study. The LDA for English and Malay achieved a perplexity of -7.31 and -7.49, respectively. Besides, the accuracy scores of SVM for English and Malay are 86.32% and 62.97%, respectively.

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1. INTRODUCTION

Electronic hailing services (e-hailing) are on-demand transportation services that allow consumers to book a ride using a mobile application. The advent of e-hailing services has introduced a new alternative in the world of public transportation, which offers a personal car service [1]. E-hailing services provide numerous advantages to consumers, such as cheaper fares, safe travel, consumer reviews, easy access, comfort, and convenience [2]. Moreover, consumers feel it is more comfortable using private vehicles, such as buses, trains, monorails, and commuters, than public transport. As a result, consumers prefer to use e-hailing services for public transportation because of their convenience and punctuality [1], [3]. In Malaysia, the demand for e-hailing services has accelerated based on increased daily travel demands [4]. More than 20 e-hailing service providers, including Grab, Maxim, and AirAsia ride, are licensed by the Land Public Transport Agency (APAD). This growing network of e-hailing services leads to intensified competition in the e-hailing industry [3], [5].

In the context of public transport services, the importance of consumer satisfaction positively influences some variables in the business organization [3], [6], [7]. If the consumers are satisfied, it proves the company provides excellent service. Otherwise, it might mean that the service does not meet the needs of the consumers. Satisfied consumers will use the e-hailing services again, become loyal to the brands and might influence others to use the same services. In other words, consumer satisfaction substantially affects the intention to use e-hailing services [4], [8]. It is influenced by service quality dimensions [9], [10] since good service quality leads to a satisfied feeling [11]. Hence, understanding the consumers' perception and satisfaction level towards the service is very important as it can help the company to improve its service and grow its business [1]. Consumer satisfaction levels can be evaluated by analyzing consumer reviews. E-hailing consumers share their feedback, opinions, and experiences through online platforms such as social media and mobile application stores.

Social media has become integral to our daily lives, changing how people communicate and gain information. X, formerly known as Twitter, recorded 5.5 million users in Malaysia in early 2023 [12]. Consumers share their thoughts and views about e-hailing on X. It has become the most popular social media site for getting information due to the availability, accessibility, and richness of content [13]. Besides, Google Play Store (GooglePS) is a mobile application store where the e-hailing application can be downloaded and installed. GooglePS allows consumers to rate these applications freely and submit their reviews and suggestions about the applications. Whether positive or negative, these reviews are critical data that give useful information to the companies and the potential e-hailing consumers for decision-making. Consumers may refer to this feedback to compare and choose the best option for e-hailing services. Consumers must analyze a large volume of opinionated data to gain better insight. Analyzing the reviews involves extracting related opinionated sentences, reading, and summarizing them, and organizing them into usable forms [14]. This task makes it difficult for humans to handle big data manually and consumes a lot of time and effort.

Sentiments are reflected in the consumer reviews by the consumer's choice of tone or expressive style [15]. These sentiments can be either positive, negative, or neutral. Analyzing sentiment from these text data is known as sentiment analysis (SA). A review might include different aspects of the entity under discussion, each with its sentiment [16], [17]. In this case, we applied aspect-based sentiment analysis (ABSA). It performs finer-grained analysis and discovers what exactly people like or dislike. Thus, ABSA is more practical as it provides exact sentiments about different aspects of entities and entities themselves, which are usually required for action [18].

Therefore, this study aims to classify and visualize the reviews about e-hailing services from GooglePS and X using ABSA. This project will classify the sentiment of reviews about e-hailing services into several aspect categories, including fare, availability, comfort, time, and convenience. These aspect categories are the service quality variables derived from previous studies that may influence consumers' intention to use the e-hailing service through consumer satisfaction.

We used two algorithms since this study involved two single ABSA tasks: aspect category detection (ACD) and aspect sentiment classification (ASC). We implemented latent Dirichlet allocation (LDA) to detect aspect categories in reviews. It is simpler to train, offers greater precision [19] and is very efficient with large corpus [20]. Additionally, the support vector machine (SVM) was applied to classify the sentiment of opinionated text. SVM was chosen for its high accuracy in diverse studies and its ability to consider various document features, including those that are often absent, mitigating information loss in the data [21], [22]. The classification algorithm will classify the reviews related to e-hailing services directly or indirectly into one of three sentiment polarities: "positive", "negative", or "neutral".

Data visualization is an essential tool to acquire valuable insight as it reveals hidden patterns, trends, and correlations between data pieces [23]. This study utilized four distinct visualization techniques: pie charts, bar graphs, line graphs and word clouds. The model was developed using datasets in English and Bahasa Malaysia to analyze the sentiment of e-hailing service reviews in both languages. The data is visualized using Plotly, an interactive plotting library for Python after the ACD and ASC are done. The results can be used to boost consumer satisfaction and retain them. Thus, consumers will explore potential new markets and effectively address any issues they encounter. This paper is organized as follows: section 1 begins with a brief introduction. In section 2 explains the methodology, followed by section 3 with result and discussion. Finally, section 4 concludes the study and provides a concise analysis of possible future enhancements.

2. RESEARCH METHOD

This research method encompasses tasks such as data collection, pre-processing, and implementation of the LDA and SVM models. Data preparation includes data acquisition and data pre-processing to ensure the reliability of collected data, followed by the application of LDA and SVM models for ACD and ASC, respectively. The output comprises visualized and reported data.

2.1. Data collection and pre-processing

A supervised machine learning model was employed for aspect sentiment classification in both English and Malay languages. Thus, a prelabelled dataset is required to train and test the model. The English dataset was retrieved from Kaggle, whereas the Malay dataset was downloaded from Github. For the model training and testing purposes, a general dataset consisting of various domains was utilized. This is because no prelabelled dataset repository related to the e-hailing service was found, and manual annotation of datasets is very time-consuming. A total of 162,980 English text data and 6,702 Malay text data were acquired.

The review dataset for the three e-hailing services, Grab, Maxim, and AirAsia Ride, was obtained from GooglePS and X (formerly known as Twitter) by utilizing Python, Google Play Scraper, and Tweet Harvest. The scrapped reviews were dated from 1 January 2023 to 31 August 2023. A total of 32,664 raw data were collected in English and Malay, with 21,290 data collected for Grab, 10,845 data collected for Maxim, and 534 data collected for AirAsia Ride. The data was finally saved in a CSV format.

The text data underwent data pre-processing. It involved data cleaning and preparation, removing irrelevant features that do not contribute value to the data analysis. To ensure consistency, all characters in the dataset were converted to lowercase, mitigating potential case-sensitive issues during pre-processing. Following this, extraneous characters like emojis, punctuation marks, and excessive whitespace were removed. Null values and duplicate reviews were eliminated from the dataset. Stop words were excluded from the data to reduce its dimensionality. Subsequently, the data underwent tokenization, involving the separation of words from the rest of the text. Following tokenization, the raw text was converted into sets of tokens, usually individual words. Then, text normalization was done separately based on the review's language through the lemmatization process. This process utilized two Python libraries: "NLTK" for English text and "nlp-id" for Malay text. This process reduces inflectional forms and sometimes derivationally related forms of a word to a common base form known as lemma. It effectively reduces the overall word count, lowering the text's dimensionality. After the pre-processing stage is completed, the final dataset is ready for the ACD and ASC. The model's evaluation will be elaborated upon in the following section.

2.2. Latent Dirichlet allocation model

LDA is an unsupervised probabilistic topic modelling technique. Its fundamental concept is that documents are depicted as stochastic combinations of latent topics, with each topic defined by a distribution across words. It aims to identify the parameters of a topic-word distribution that maximizes the likelihood of documents in the dataset across a given number of topics. Due to LDA's emphasis on the significance of each topic in every document it learns, it becomes feasible to ascertain which topic composition most accurately captures the essential content of each document [24]. Pathan and Prakash [19] also supported the idea that it is more precise, easier to train, and capable of inferring topics from a given collection effortlessly without using prior knowledge as input, making LDA the most common topic modelling technique employed in real-world scenarios.

Following the text pre-processing steps, a document-term matrix (DTM) was constructed with a Python library for topic modelling known as Gensim. The step was accomplished by converting the pre-processed real-world data into a dictionary and corpus. The dictionary establishes a mapping between words and their corresponding integer IDs. In contrast, the corpus is a list of documents expressed in a BOW format. Next, the LDA model was trained on the previously created DTM with the number of topics specified as 5 to generate five distinct topics, with each topic being a combination of keywords. These steps were done for two datasets: English and Malay. The topics were then mapped to the five aspect categories, namely fare, availability, comfort, time, and convenience, by referring to the keywords of each topic.

2.3. Support vector machine model

SVM is a non-probabilistic supervised ML algorithm. It identifies an optimal hyperplane with the maximized margin to separate the data into distinct classes. SVM could achieve high performance in practical applications as it is relatively easy to analyze mathematically, yet it can effectively handle complex models [25]. Before the SVM model can be applied to real-world review data, the SVM algorithm needs to be trained with the prelabelled dataset since it is a supervised ML algorithm. As illustrated in Figure 1, the process of training and testing the SVM algorithm began with data preparation, encompassing the data collection and data pre-processing. The prelabelled datasets for English and Malay models were acquired from Kaggle and GitHub. These datasets were then pre-processed through case transformation, tokenization, stop words and noise removal, and lemmatization, as explained in section 2.4.

The prelabelled datasets were split into training and testing sets with an 80:20 ratio, where 80% constituted the training data, and the remaining 20% formed the testing data. To ensure sufficient training data, the testing set should not exceed the size of the training set. The seed for the random number generator, crucial for randomness, was set to 42. Both training and testing sets were then transformed into numerical vectors using TF-IDF. TF-IDF is a weighted statistical method for evaluating the importance of words to text.

Its weighting process improves the term retrieval effectiveness [26]. Term frequency (TF) counts the occurrences of a phrase in a document, while inverse document frequency (IDF) gauges its relevance. Formulas for TF, IDF, and TF-IDF are defined in (1), (2), and (3), respectively.

$$TF(t,d) = \frac{Number\ of\ occurence\ of\ term,t\ in\ document,d}{Total\ number\ of\ terms\ in\ document,d} \quad (1)$$

$$IDF(t) = \log\left(\frac{Total\ number\ of\ documents}{Number\ of\ documents\ with\ term,t}\right) \quad (2)$$

$$TF\text{-}IDF(t,d) = TF(t,d) \times IDF(t) \quad (3)$$

Following the splitting and vectorization process, the SVM classification model was established by calling the function “svm.LinearSVC()” and was trained with the feature vector and the target variable as inputs. This process is commonly known as the training process. Next, a prediction can be generated for the test dataset. The model’s accuracy in predicting the test dataset is presented as a percentage of correct predictions relative to the total number of predictions generated by the model.

2.4. Model deployment

Model deployment is the process of putting the developed models into practical use. In many instances, it involves making a model accessible through real-time APIs, allowing for the retrieval of information in real-time. During the deployment stage, the LDA model clustered the collected reviews with topic numbers of “0”, “1”, “2”, “3”, and “4”. The values were then mapped with the aspect categories based on the topics generated by the model, as presented in Figure 2 and Figure 3.

On the other hand, the SVM model was ready for deployment. Before the SVM model could perform the sentiment classification of the real-world review data, the data underwent a vectorization process using TF-IDF. Once it was transformed into numerical formats, the SVM model classified the real-world review data with sentiment labels of “-1,” “0,” and “1,” corresponding to negative, neutral, and positive sentiments, respectively.

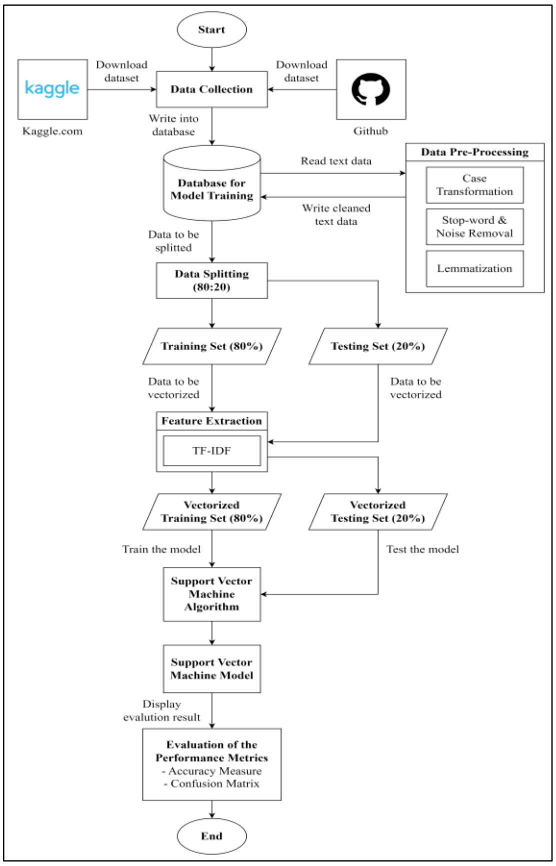


Figure 1. Flow diagram for the training and testing process of SVM model

After applying the models to make predictions based on the acquired data and evaluating its performance, the data was visualized using Plotly, an open-source interactive graphics library for Python. Charts were produced using the chart studio in the online version of Plotly, along with the entered data. The outcome was then employed in constructing an interactive visualization tool that presented the results of real-world data analysis.

Word cloud data visualization was utilized to represent the text data for e-hailing services generated by the system. Words were displayed in various colors, and the size of each word emphasizes its frequency in the text data. The terms associated with e-hailing services are readily identifiable due to their placement in the word cloud.

	Topic_Number	Topic_Name	Top_Keywords
0	0	Convenience	['card', 'use', 'cant', 'money', 'payment', 'pay', 'account', 'phone', 'number', 'try']
1	1	Comfort	['good', 'service', 'thank', 'great', 'friendly', 'driver', 'fast', 'nice', 'thanks', 'much']
2	2	Price	['driver', 'order', 'time', 'cancel', 'get', 'wait', 'book', 'even', 'take', 'car']
3	3	Time	['service', 'customer', 'bad', 'location', 'help', 'map', 'use', 'support', 'chat', 'issue']
4	4	Availability	['use', 'price', 'easy', 'cheap', 'get', 'like', 'best', 'high', 'well', 'way']

Figure 2. Topics generated by English LDA model

	Topic_Number	Topic_Name	Top_Keywords
0	0	Convenience	['murah', 'driver', 'order', 'cancel', 'drivernya', 'gak', 'udah', 'banget', 'aja', 'pilih']
1	1	Fare	['terima', 'kasih', 'nak', 'harga', 'murah', 'bantu', 'pandu', 'tambang', 'mantap', 'driver']
2	2	Fare	['harga', 'teruk', 'bintang', 'urus', 'mahal', 'pakai', 'mas', 'bad', 'dlm', 'jangkau']
3	3	Convenience	['driver', 'bagus', 'susah', 'bayar', 'tolong', 'map', 'titik', 'order', 'cari', 'terimakasih']
4	4	Comfort	['baik', 'ramah', 'puas', 'cepat', 'pandu', 'hati', 'mudah', 'layan', 'bersih', 'kereta']

Figure 3. Topics generated by Malay LDA model

3. RESULTS AND DISCUSSION

3.1. Model performance

The assessment of model performance is crucial for ensuring its effectiveness and reliability. It involves evaluating how effectively a predictive model achieves specified goals and provides accurate predictions for new, unseen data. A comprehensive understanding of model performance is essential for well-informed decision-making and determining the model's effectiveness in real-world applications.

Various metrics and evaluation techniques are employed to gauge the performance of a model. These assessments typically include measures such as accuracy, precision, recall, and F1-score. Each metric provides insights into distinct aspects of the model's performance, allowing it to gain a comprehensive understanding of its strengths and weaknesses.

3.1.1. Perplexity and coherence score of latent Dirichlet allocation models

Perplexity and coherence scores were used as the evaluation metrics to assess LDA performance. Perplexity is a measure of how well the topic model predicts new or unseen data. A lower perplexity score signifies that the model has a better performance [27]. Based on Figure 4, the Perplexity of English and Malay LDA models are -7.31 and -7.49, respectively. Although the Perplexity of both models is below 0, the perplexity of the Malay LDA model is slightly lower than the English LDA model. It indicates that the ability of the Malay LDA model to accurately predict the aspect category of e-hailing reviews is slightly better than that of the English LDA model.

On the other hand, the coherence score indicates the level of semantic similarity between words on a topic. It is measured on a scale from 0 to 1, where a higher value means substantial similarity and that the topic is consistent, clear, and relevant [28]. As shown in Figure 5, the coherence scores of English and Malay LDA models are 0.58 and 0.49, respectively. The coherence scores of both English and Malay LDA models are in the middle of the range between 0 and 1. However, the coherence of the English LDA model is slightly higher than the Malay LDA model. It indicates that the degree of similarity between keywords for each topic of the English LDA model is slightly higher than that of the Malay LDA model. It can be influenced by the length of reviews and the chosen number of topics. Short reviews lack context to discern meaningful topics, and too few topic numbers may lead to a lower coherence score. Additionally, it can also be due to fuzzy topics that include many different terms or overlap semantically with other topics [29].

3.1.2. Accuracy of support vector machine models

In order to evaluate the accuracy of the SVM classifier model, its performance is measured by comparing predicted values with actual values extracted from a test dataset. Table 1 shows that the English SVM model achieved an accuracy score of 86.32%. Meanwhile, the accuracy score derived from the Malay SVM model was 62.97%. In this study, the confusion matrix assigns the class "negative" to the number -1, "neutral" to 0, and "positive" to 1.

Musgrave [30], an accuracy score exceeding 90% is considered "Excellent," while scores between 70% and 90% are labelled "Good." Accuracy ranges between 60% and 70% is deemed "Okay," and anything below 60% is considered "Poor." Thus, the accuracy of the English SVM model falls within the "Good" range, while that of the Malay SVM model is regarded as "Okay".

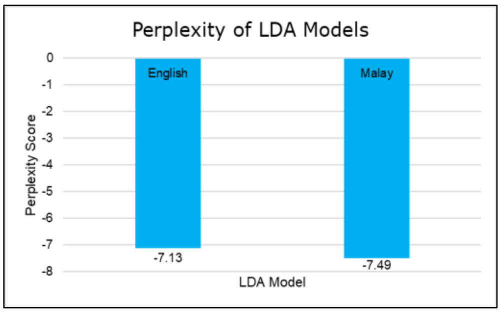


Figure 4. The Perplexity of English and Malay LDA models

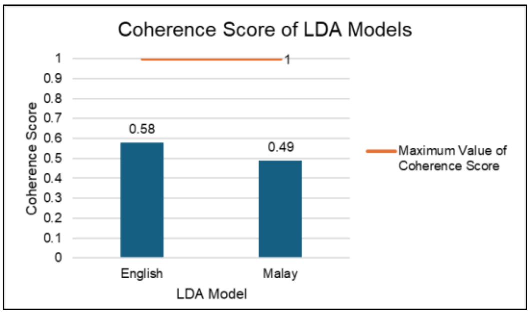


Figure 5. The coherence score of English and Malay LDA models

Table 1. Results of accuracy, precision, recall and F1-score for English and Malay

Malaysia's e-hailing perception for English and Malay				
Language	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
English	86.23	84.00	93.00	88.00
Malay	62.97	54.00	71.00	70.00

3.2. Analysis of aspect categories

3.2.1. Overall ABSA

The complete data analysis was visualized using data visualization techniques such as pie charts, bar charts, line charts and word clouds for better vision. Table 2 shows the comparison of sentiment results for all e-hailing services, where out of the total of 17,257 sentiments, it was distributed to 10,230 positive, 3,786 negatives and 3,241 neutral sentiments. Figure 6 shows the bar chart of the total sentiments of three e-hailing services in the dataset, where it exhibits a higher frequency of positive mentions than neutral and negative mentions. The user may immediately compare positive, negative, and neutral sentiments using the pie chart's percentage value and color differences, as in Figure 7.

The aspect categories based on five aspect categories, including fare, availability, comfort, time, and convenience, are visualized in the bar graph, as in Figure 8. Users may visualize the total mentions of each e-hailing service based on specific aspect categories. Fare shows the highest-mentioned sentiments for all e-hailing services, and time shows the lowest-mentioned sentiments. A stacked bar graph breaks down the analysis of the e-hailing service's aspect categories based on sentiment polarities, as in Figure 9. Users may visualize the total sentiments based on e-hailing services for each aspect category.

Table 2. Comparison of results for Grab, Maxim, and AirAsia ride

e-hailing service	Number of reviews	Number of positive reviews	Number of negative reviews	Number of neutral reviews
Grab	11,042	6,114	2,729	2,199
Maxim	5,748	3,902	895	951
AirAsia ride	467	214	162	91
Total	17,257	10,230	3,786	3,241

3.2.2. Word cloud ABSA

In Figure 10 shows the word cloud ABSA visually for three sentiment polarities. The size of each term reflects its frequency in the dataset. Larger sizes correspond to higher occurrence frequencies. Figure 10(a) represents positive sentiment text data. Noteworthy positive expressions like "good," "*baik*," "great," and "easy" are featured in the word cloud, highlighting their association with positive sentiments. Figure 10(b) depicts a visualization highlighting phrases associated with negative sentiment. The word cloud includes terms like "bad," "*susah*," "expensive," and "useless." Figure 10(c) exhibits the word cloud representing neutral emotions. This visualization highlights terms associated with neutral mentions such as "order", "cancel", and "driver".

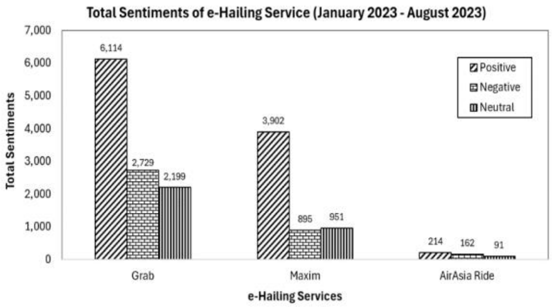


Figure 6. Bar chart of the total sentiments e-hailing services

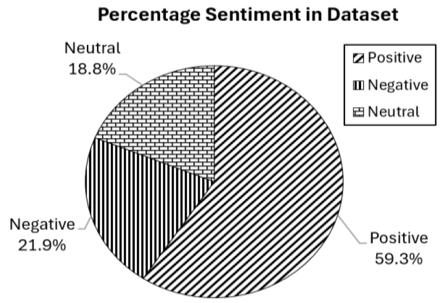


Figure 7. Pie chart of percentage sentiment in dataset

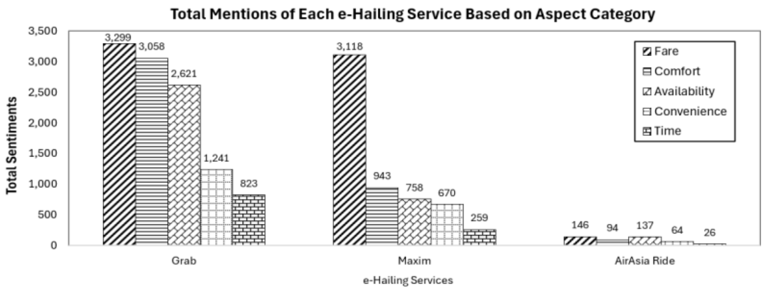


Figure 8. Bar chart for total mentions of e-hailing services based on aspect category

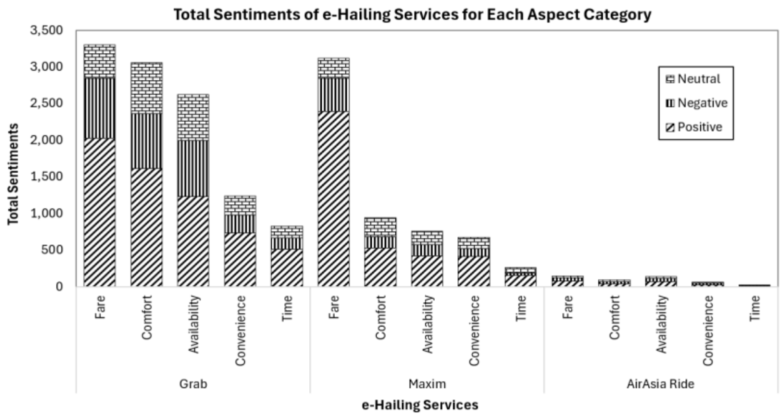
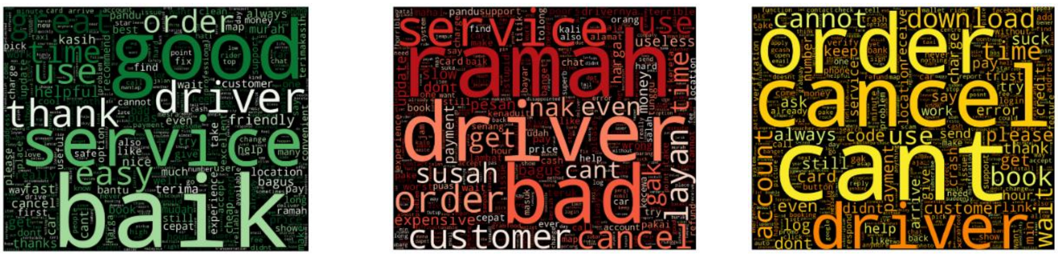


Figure 9. Stack bar chart for total sentiments of e-hailing services for each aspect category



(a) (b) (c)

Figure 10. Word clouds for (a) positive sentiments, (b) negative sentiments, and (c) neutral sentiments

4. CONCLUSION

In this study, a web-based application was designed and developed to classify the reviews of Malaysia's e-hailing services: Grab, Maxim, and AirAsia Ride. The visualization of ABSA was extracted from GooglePS and X from 1st January 2023 to 31st August 2023. Users can utilize the embedded LDA and SVM models on any text data within the system. The data collected through the application aids users in evaluating the performance of e-hailing services and making informed decisions for the future. In addition, the web-based application incorporates various visualizations, facilitating a clear understanding of the e-hailing services available in Malaysia. This visualization feature enables consumers to efficiently compare different e-hailing options, saving them time and effort while gaining more accurate insights. Moreover, it offers a more detailed comparison of the e-hailing services based on five aspects, including fare, availability, comfort, time, and convenience. Hence, it improves consumers' decision-making by allowing them to obtain quick and deeper insights. It is recommended that in the future, the evaluations of Malay reviews be meticulously examined one by one to ensure the absence of Indonesian words. Next, more information can be expanded by scraping from other sources such as Facebook or Threads and by prolonging the duration of data scraping. Given that emojis convey users' intentions in expressing their opinions, integrating them into the classification process is essential.

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