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ENHANCING USER INSIGHTS: A VISUALIZATION DASHBOARD FOR ASPECT-BASED SENTIMENT ANALYSIS OF MALAYSIA'S ISLAND TRAVEL AGENCIES

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Article Info

Abstract

Island travel agencies are growing in popularity in Malaysia, leading to increased competition. Traveler satisfaction is crucial for business success, and platforms like Google Maps and Facebook provide valuable reviews for evaluation. However, these reviews are often unstructured and difficult to analyze. This project aims to develop a web application using Aspect-Based Sentiment Analysis (ABSA) to classify and visualize reviews for island travel agencies in Malaysia. The system employs Naïve Bayes (NB) for sentiment classification and Latent Dirichlet Allocation (LDA) for aspect detection, focusing on four categories: price, guide, experience, and service. Results are displayed through pie charts, word clouds, bar charts, and line charts. The system was tested for accuracy, functionality, and usability. LDA achieved a coherence score of 0.428, while NB achieved 93.40% accuracy for English and 77.32% for Malay. Usability testing was conducted using the Usability Metric for User Experience (UMUX), yielding an overall satisfaction score of 92.50%, with high ratings for effectiveness, satisfaction, and efficiency, indicating exceptional usability. Future improvements include extending data scraping, and incorporating data from platforms like Trivago and Agoda. The system is highly effective, user-friendly, and provides valuable insights for travelers and agencies.

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INTRODUCTION

Malaysia's travel industry contributes greatly to the nation's economy, and island touring is extremely in vogue amongst domestic and foreign visitors. Tourist island operators have sprouted in number, leading to competitive forces where it is difficult to pick the top operator amidst several options available, due to there being numerous packages on offer. People employ social media like Google Maps and Facebook for ratings but, given a plethora of users, manually breaking down the rating becomes an absolute impossibility. Sentiment Analysis (SA) helps estimate public opinion, whereas Aspect-Based Sentiment Analysis (ABSA) categorizes sentiments based on aspects like price, experience, guide, and service (Moon & Han, 2019). Google Maps and Facebook can be helpful customer satisfaction sources, but the open-ended nature of reviews makes it hard to reach meaningful conclusions. Customers struggle with biased or contradicting comments, and agencies struggle to handle bulk reviews. Naïve Bayes (NB) is effective in sentiment classification since it is efficient and straightforward (Ramadhani et al., 2021), while Latent Dirichlet Allocation (LDA) identifies salient themes from text data (Pallawala, 2023). This study suggests an automatic web-based system that conducts sentiment classification and visualizing Google Maps and Facebook data using LDA for aspect detection and NB for sentiment classification. The system provides data in pie charts, bar graphs, and word clouds, allowing tourists to make sound decisions and helping agencies improve services through data-driven insights.

LITERATURE REVIEW

The literature review explores existing studies relevant to sentiment analysis, particularly Aspect-Based Sentiment Analysis (ABSA) and its application in the tourism industry. This section provides an overview of island travel agencies in Malaysia, discussing how digital platforms influence traveler decisions. It also examines various sentiment analysis techniques, highlighting the role of machine learning approaches such as Naïve Bayes (NB) in classifying user-generated reviews. Additionally, the review covers text preprocessing methods, including word retrieval algorithms like TF-IDF, and emphasizes the significance of visualization techniques in presenting sentiment results. By examining related works, this chapter identifies research gaps and justifies the need for an ABSA-based sentiment analysis system tailored to island travel agencies.

Overview of Island Travel Agencies in Malaysia

Malaysia is home to many island travel agencies that provide essential services to tourists, including accommodation, transportation, and guided tours. These agencies play a significant role in promoting tourism by offering customized travel packages to popular island destinations such as Mabul, Redang, and Tioman (Moon & Han, 2019). With the growing reliance on digital platforms as depicted in Figure 1, these agencies have adopted online marketing strategies and integrated customer review systems to improve their services and attract more visitors.

Traveler's Intention in Choosing an Island Travel Agency

Several factors influence travelers' decisions when selecting an island travel agency. These factors include service quality, pricing, past customer experiences, and the availability of tour guides (Kim, 2023). Online reviews have become a crucial element in travelers' decision-making processes, as they provide insights into previous customers' experiences and help potential clients assess the reliability of a travel agency (Gupta et al., 2022). Sentiment analysis of these reviews enables a better understanding of what aspects matter most to travelers.

Aspect-Based Sentiment Analysis (ABSA)

ABSA is a refined method of sentiment analysis that allows for a more detailed evaluation of customer feedback by categorizing sentiments based on specific aspects (J et al., 2022). This method helps businesses and researchers analyze customer opinions on different components of a service rather than assessing overall sentiment. In this study, ABSA is applied to reviews from Google Maps and Facebook, classifying them into four primary aspects such as service, experience, guide, and price. The final aim of ABSA is to accurately annotate sentences with specific aspects (Nuha & Lin, 2023)

Machine Learning Approaches

Various machine learning techniques have been employed for sentiment analysis, with supervised learning methods such as Support Vector Machines (SVM), Decision Trees (DT), and Naïve Bayes (NB) being the most common (Ramadhani et al., 2021). Among these, NB is widely used due to its efficiency, ability to handle large datasets, and effectiveness in classifying text-based data (H. Gao, 2023). In this study, NB is chosen for its high accuracy in sentiment classification tasks. The general form of NB is formulated in Equation 1.

$$P(C|X) = \frac{P(X|C)P(C)}{P(X)} \quad (1)$$

Word Retrieval Algorithms

Text preprocessing is an essential step in sentiment analysis, involving the use of word retrieval algorithms to extract meaningful terms from raw text data. Common techniques include Term Frequency-Inverse Document Frequency (TF-IDF) and Rapid Automatic Keyword Extraction (RAKE) (Mathayomchan & Sripanidkulchai, 2019). TF-IDF is utilized in this study for its ability to highlight significant keywords that contribute to sentiment classification. The TF value is calculated, representing the frequency of each term that will appear in a document, which is computed as the number of times the word appeared against the overall total numbers of words in a document. This is expressed mathematically in Equation 2 below. IDF scores the importance of terms taking a logarithm from the total amount of documents upon the number of documents containing this word plus one, presented in Equation 3. The multiplication of the two values results in Equation 4, showing the TF-IDF

$$TF(t,d) = \frac{Num. of\ times\ term\ t\ appears\ in\ document}{Total\ terms\ in\ document\ d} \quad (2)$$

$$IDF(t,D) = log\left(\frac{N}{Num. of\ documents\ contain\ term\ t + 1}\right) \quad (3)$$

$$TF\text{-}IDF(t,d,D) = TF(t,d)\ \times IDF(t,D) \quad (4)$$

Development Approaches

Various machine learning techniques have been employed for sentiment analysis, with supervised learning methods such as Support Vector Machines (SVM), Decision Trees (DT), and Naïve Bayes (NB) being the most common (Ramadhani et al., 2021). Among these, NB is widely used due to its efficiency, ability to handle large datasets, and effectiveness in classifying text-based data (H. Gao, 2023). In this study, NB is chosen for its high accuracy in sentiment classification tasks.

Visualization Techniques

The effectiveness of sentiment analysis depends on how well the results are presented. Visualization techniques such as pie charts, bar graphs, word clouds, and line charts help users understand sentiment trends more intuitively (Roy & Ojha, 2020). This project incorporates these visualization techniques to display ABSA results, enabling better interpretation of customer feedback.

METHODOLOGY

This section divides the methodology for the ABSA of island travel agencies reviews into development phases and the system design

Development Phase

Figure 1 shows the five phases of developing the visualization dashboard for the ABSA of Malaysia's e-hailing reviews using a modified waterfall methodology: requirement, design, implementation, testing, and deployment (Kartika et al., 2022). Each phase consists of a specific task to be completed. This paper focuses on the usability test of the visualization dashboard for the ABSA of Malaysia's e-hailing reviews.

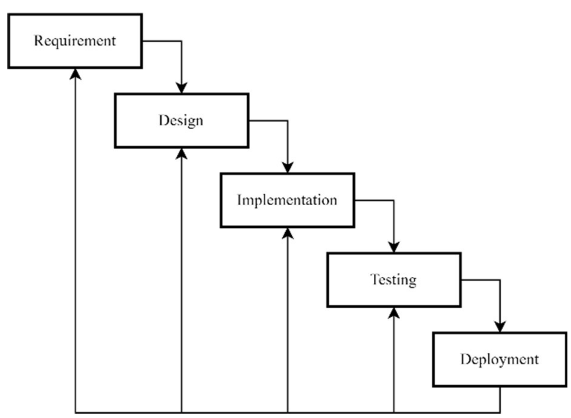

Figure 1: Phase Involved in Developing

In this project, a two-stage method ABSA was performed, where ACD and ASC tasks were done separately. The Latent Dirichlet Allocation (LDA) model is utilized for ACD, whereas the Support Vector Machine (SVM) classifier model is employed for ASC. LDA emphasizes the significance of each topic in every document it learns, making it feasible to ascertain which topic composition most accurately captures the essential content of each document (Tseng et al., 2019). Meanwhile, NB could achieve high performance in practical applications as it is relatively easy to analyze mathematically, yet it can effectively handle complex models (Reddy P et al., 2023).

System Design

In the design phase, we created a use case diagram to illustrate the system's functional requirements from the user's perspective. In addition, we designed a user interface to describe how users interact with the system. Then, we used the flowchart in Figure 2 to show the system’s process flow.

The process begins by directing the user to the system's landing page. When the user clicks the “GET STARTED” button, they are navigated to the home page, which provides background information on each island travel agencies. The next section is the "Dashboard," where users can view a summary of Island Travel Agencies services for 2022 and above. This page includes the total sentiment for all nine agencies, a sentiment pie chart, and a bar chart summarizing the analysis across five key aspects

Users who select " SDC Mabul " are taken to a page displaying SDC Mabul’s visualized data. Similarly, clicking “Arung Hayat Sea Adventures”, “Nafida Holidays Sdn. Bhd.”, “Jeti Penarik Ke Pulau Redang, Redang Reef Resort Travel & Tours Sdn. Bhd.”, “Tioman Dadini Snorkeling”, “Qoshki Dive Team”, or “Udive Tioman” redirects the user to respective pages with visualized data. The “Aspect Analysis” is to visualize the aspect details. The "Competitive Analysis" feature allows users to view and compare results for all three agencies. “Sentiment Analyzer” allows users to insert text and system will analyze the text. Lastly, the "Sample Reviews" section directly displays all the sample reviews from each island travel agencies.

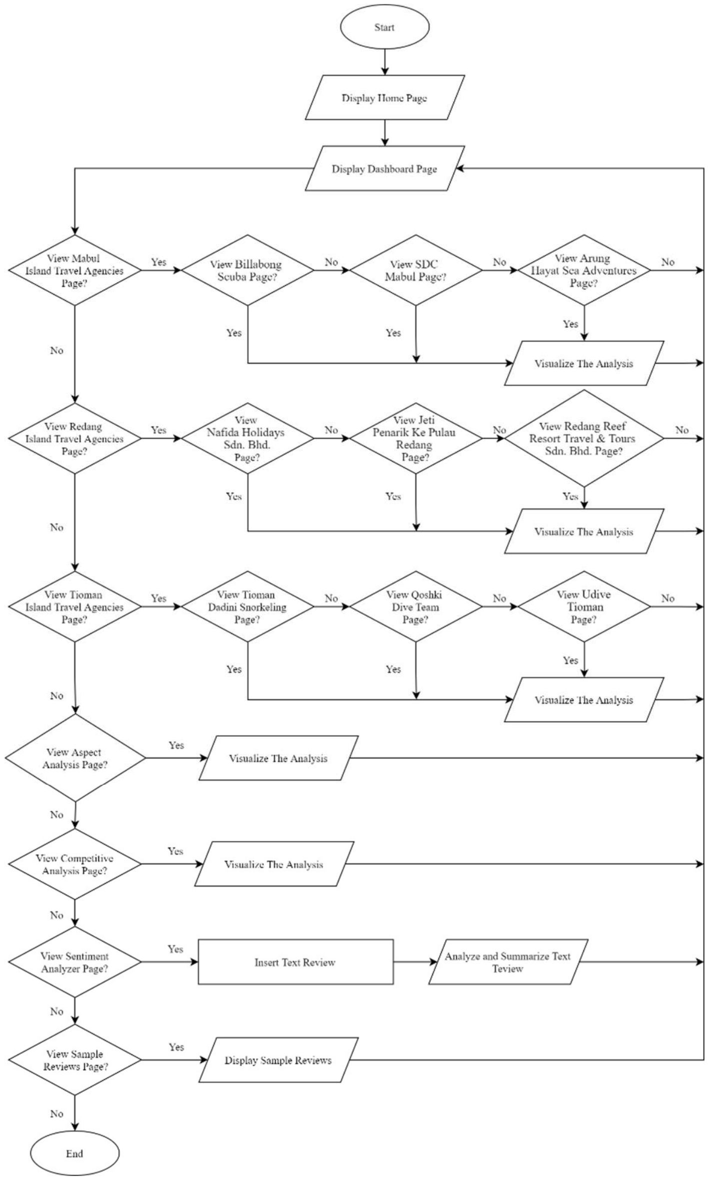

Figure 2: Flowchart Diagram of the System

Usability Metric for User Experience

Since the project is related to island travel agencies, this system can be used by every individual, allowing for a large-scale usability test. Face-to-face usability testing based on UMUX was conducted, where users assessed the system on a particular computer under observation. A total of 30 participants took part in the UMUX testing. Among them, 17 were students, while the remaining participants were lecturers and individuals from other professions. Participants were assigned tasks such as rating the system’s attributes. A questionnaire was distributed via Google Forms to collect responses, which comprised user information such as names and occupations and their experience with the system. Figure 3 illustrates the procedures used to conduct the system usability test.

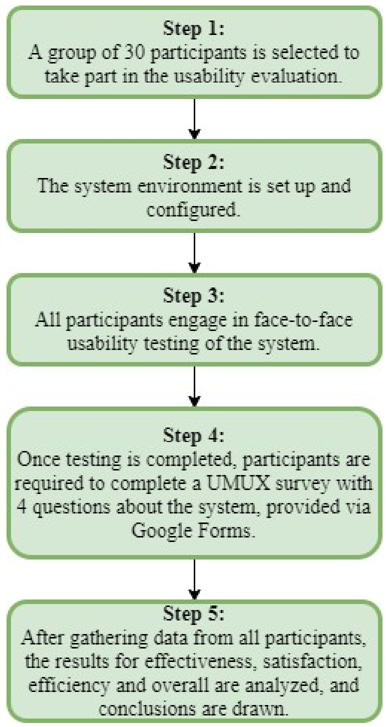

Figure 3: Procedure for Conducting UMUX Testing for the System

After the respondents have completed their testing and observation of the system, each participant will receive a four-question UMUX questionnaire. This questionnaire uses a 7-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree", to capture detailed feedback on their experiences with the system that focuses on usability and user satisfaction. The results from the UMUX questionnaire will be used for further analysis to identify areas for improvement. The questionnaire is divided into four components that are effectiveness, satisfaction, efficiency, and overall use of the system. Then, the UMUX scores are calculated by averaging the scores of the four questions and then converting this average to a percentile rank to interpret the usability level.

The overall UMUX and its component results are determined by analyzing the collected data. This analysis includes calculating the mean scores for each subcomponent and the overall score. It can be done by combining the scores of the positively worded items and the transformed scores of the negatively worded items related to usability and learnability. Then, the mean of the total scores from all four items is calculated. Furthermore, Q1 and Q3 are odd-numbered components that need to be reversed because they are positively worded. The reversed and UMUX scores can be calculated as shown in Equation 5 and Equation 6

$$Reversed\ Score = 7 - Original\ Score + 1 \tag{5}$$

$$UMUX\ Score = [Q1 - 1] + [Q3 - 1] + [7 - Q2] + [7 - Q4]\ (\frac{100}{24}) \tag{6}$$

Since the UMUX testing does not compute individual subcomponent scores for effectiveness, efficiency, and satisfaction, as SUS does, computing them as averages across the respective items. The UMUX simplifies it even further. Inasmuch as UMUX replaces SUS, the method of computation used for the subcomponents of SUS can be extended to UMUX. For this research, Equation 7 is used to translate the method of SUS-based analysis into the context of UMUX (Faradina et al., 2022). This will ensure consistent measurement of the user experience while reaping some advantages of UMUX for improved usability testing results.

$$UMUX\ Subcomponent\ Score = 100 - (Average\ Score - 1)(\frac{100}{6} \tag{7}$$

RESULT AND DISCUSSION

This section elucidates the findings and outcomes of the suggested study of the Aspect-Based Sentiment Analysis Classification of Google Maps and Facebook Reviews for Island Travel Agencies Using Naïve Bayes. It is divided into two categories. The ABSA dashboard interface for island travel agencies and usability test findings.

ABSA of Malaysia's Island Travel Agencies Dashboard User Interface

A user interface (UI) 's primary function is to facilitate user interaction with a system. This interaction includes entering inputs, navigating menus, managing data, and receiving outputs. Figure 4 shows the "Overall Dashboard Page", visualizing the total sentiment, word clouds and bar charts summarizing the results of ABSA.

Figure 4: Overall Dashboard Page

Figure 5 depicts the "Competitive Analysis Page", displaying the visualizations that compare the analysis results between three island travel agencies.

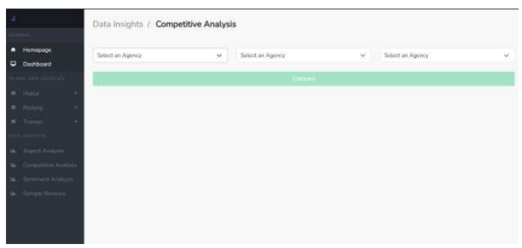

Figure 5: Competitive Analysis Page

Figure 6 displays the "Sentiment Analyzer Page", displaying the tool that analyze the sentiment when user input text review.

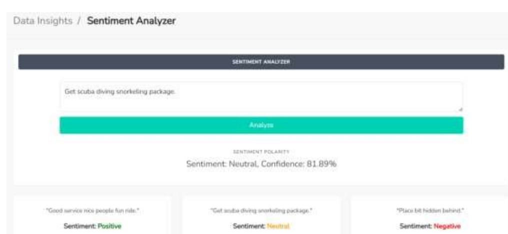

Figure 6: Sentiment Analyzer Page

Usability Testing

The questionnaire responses show differing views of the participants. The frequency table shown in Figure 7, which is based on UMUX survey questions, shows the frequency of response data collected with the aid of Google Forms. Most of the users responded with "strongly agree" to UMUX statements, meaning they find the system friendly and effective without technical assistance. The overall findings show high levels of user satisfaction.

No.	Full Name	Q1	Q1 Reversed	Q2	Q3	Q3 Reversed	Q4	Score of UMUX Odd Score: [Q1-1]+[Q3-1]	Score of UMUX Even Score: [7-Q2]+[7-Q4]	UMUX Score	Adjective
1	NUR HAZIQAH	7	1	2	6	2	2	11	10	87.50	Excellent
2	FARAH ALYSA	7	1	1	6	2	1	11	11	91.67	Best Imaginable
3	MUHAMMAD NAZRIN	7	1	2	7	1	1	12	11	95.83	Best Imaginable
4	MOHAMAD HALID SAZLI	6	2	1	7	1	2	11	12	95.83	Best Imaginable
5	HUDA AFIQAH	6	2	1	7	1	2	11	11	91.67	Best Imaginable
6	FARRAH KAMILIA	6	2	2	6	2	2	10	10	83.33	Excellent
7	MUHAMMAD 'AZIM	7	1	1	6	2	1	11	12	95.83	Best Imaginable
8	NUR FATIN HIDAYAH	6	2	2	6	2	2	10	10	83.33	Excellent
9	MUHAMMAD FIRDAUS	7	1	1	7	1	1	12	12	100	Best Imaginable
10	AHMAD SAIFUDDIN	6	2	2	7	1	1	11	11	91.67	Best Imaginable
11	MUHAMMAD FARIS IRFAN	6	2	2	7	1	1	11	11	91.67	Best Imaginable
12	MUHAMMAD HAFIZUDDIN	6	2	2	6	2	2	10	10	83.33	Excellent
13	IRFAN DZAFRI	7	1	1	7	1	1	12	12	100	Best Imaginable
14	ERZIQ AIMIEN	6	2	1	7	1	1	11	12	95.83	Best Imaginable
15	NURUL AIN NAJWA	6	2	1	7	1	1	11	12	95.83	Best Imaginable
16	AMNI NURHANA	7	1	1	7	1	1	12	12	100	Best Imaginable
17	ZAINAL	6	2	3	6	2	2	10	9	79.17	Good
18	NIK SYAZWAN	6	2	2	7	1	1	11	11	91.67	Best Imaginable
19	MUHAMMAD SYUKRI	6	2	1	7	1	1	11	12	95.83	Best Imaginable
20	MAZITA	7	1	1	7	1	1	12	12	100	Best Imaginable
21	MUHAMMAD MUZZAMMIL	7	1	2	7	1	1	12	11	95.83	Best Imaginable
22	BAHRUM	7	1	2	6	2	2	11	10	87.50	Excellent
23	MUHAMMAD LUQMAN	7	1	1	7	1	2	12	11	95.83	Best Imaginable
24	NUR ATHIRAH	7	1	1	7	1	1	12	12	100	Best Imaginable
25	PUTERI SYARAFANA	7	1	1	7	1	1	12	12	100	Best Imaginable
26	KHYRIN FARIZAL	7	1	2	7	1	1	12	11	95.83	Best Imaginable
27	NADIA NUR	7	1	1	7	1	1	12	12	100	Best Imaginable
28	KHAIRUDDANISH	6	2	2	7	1	2	11	10	87.50	Excellent
29	FARIDAH NURDINIE	7	1	2	7	1	1	12	11	95.83	Best Imaginable
30	MUHAMMAD NAZHAN	6	2	1	7	1	1	11	12	95.83	Best Imaginable
	Average		1.47	1.50			1.20			92.50	Best Imaginable

Figure 7: Competitive Analysis Page

The researcher Hermawan et al. (2023) explains that the scores of UMUX questions were averaged based on the score measurement rules in Table 1 to calculate the mean scores of each subscale. Lower mean scores indicate a higher level of user experience. The scores were further normalized into percentage values, allowing the interpretation of the scores in SUS norms. The UMUX scores were interpreted based on the scale in Table 1 and Table 2. The acceptability level and the adjective rating were obtained to clarify the usability level of the visualization dashboard for ABSA of island travel agencies.

Table 1: The UMUX Components and Candidate Items

Component	Odd/Even	Candidate UMUX Items
Effectiveness	Odd	This system's capabilities meet my requirements.
Satisfaction	Even	Using the system is a frustrating experience.
Overall	Odd	This system is easy to use.
Efficiency	Even	Wasting too much time correcting things.

Table 2: The UMUX Acceptability Measurements Range

UMUX Score	Percentile Range	Grade	Adjective	Acceptable
90-100	90-100	A	Best Imaginable	Acceptable
80-89	80-89	B	Excellent	Acceptable
70-79	70-79	C	Good	Acceptable
60-69	60-69	D	OK	High Marginal
50-59	50-59	F	OK	Low Marginal
40-49	40-49	F	Poor	Not Acceptable
30-39	30-39	F	Poor	Not Acceptable
20-29	20-29	F	Worst Imaginable	Not Acceptable
10-19	10-19	F	Worst Imaginable	Not Acceptable
0-9	0-9	F	Worst Imaginable	Not Acceptable

Table 3 shows the System Effectiveness subscale results obtained from the UMUX survey Q1 Reversed. The final UMUX effectiveness score calculated from Equation 7 reaches 92.17% which corresponds to Grade A or Best Imaginable based on an average score of 1.47. The system receives high marks for its excellence in fulfilling user requirements by delivering a smooth functional interface.

Table 3: System Effectiveness Result

Metric	Average Score	UMUX Subcomponent Score (%)	Grade	Adjective
Effectiveness (Q1 Reversed)	1.47	92.17%	A	Best Imaginable

Table 4 contains the System Satisfaction subscale data from the Q2 column of the UMUX survey. The 1.50 score calculated into the effectiveness score using Equation 7 results in 91.67% that qualifies for Grade A or Best Imaginable. The system appears able to users as well as efficient which creates a favorable user experience.

Table 4: System Satisfaction Result

Metric	Average Score	UMUX Subcomponent Score (%)	Grade	Adjective
Satisfaction (Q2)	1.50	91.67%	A	Best Imaginable

In Table 5, the results of the UMUX survey for the System Satisfaction subscale which is from column Q4. The average score is 1.20, translating to a final UMUX effectiveness score of 96.67% by using Equation 7, which falls under Grade A or Best Imaginable, suggesting that users found the system easy to navigate and efficient for task completion.

Table 5: The Efficiency Result

Metric	Average Score	UMUX Subcomponent Score (%)	Grade	Adjective
Efficiency (Q4)	1.20	96.67%	A	Best Imaginable

The overall score for UMUX acceptability measurements for this project is 92.50, as presented as the average UMUX score in Figure 7. This score falls within the 90-100 percentile range that is graded as "A" and described as "best imaginable," which means that the project has the highest level of acceptability for the usability of the system.

CONCLUSION

The web-based dashboard uses aspect-based sentiment analysis of Google Maps and Facebook reviews with Naïve Bayes to help users evaluate Malaysian island travel agencies. It provides visualizations like pie charts, word clouds, bar charts, and line charts, allowing users to compare agencies easily and gain useful insights. The system analyzes four key aspects: price, service, guide, and experience, helping travelers make informed decisions quickly. Future improvements include better data visualization using percentages and expanding usability testing beyond 35 participants to include a more diverse user group for a more thorough evaluation.

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