JHSS (Journal of Humanities and Social Studies)
https://journal.unpak.ac.id/index.php/jhss
Volume 09, Number 01, Page 065-071
e-ISSN: 2598-120X; p-ISSN: 2598-117X

ANALYSIS OF MYPERTAMINA SERVICE DESIGN TO IMPROVE SERVICE QUALITY

Moch. Rafie Pratama [a)], Wiwik Handayani [a*)]

[a)]*Universitas Pembangunan Nasional 'Veteran' Jawa Timur, Surabaya, Indonesia*

[*)]*Corresponding Author: wiwik.em@upnjatim.ac.id*

Article history: *received 12 June 2025; revised 18 June 2025; accepted 30 June 2025* *DOI: https://doi.org/10.33751/jhss.v9i1.49*

Abstract. The public's dependence on fuel oil (BBM) makes it a vital component in supporting the smooth production and distribution of goods and services, as well as maintaining economic stability. However, it is estimated that around 30 percent of energy subsidies have been enjoyed by groups that are not classified as poor or vulnerable. To address this issue, PT Pertamina (Persero) has implemented a new policy requiring vehicle registration through the MyPertamina app for users of subsidized fuels such as Pertalite and Solar. However, many users have expressed complaints regarding the operational aspects of the app. Therefore, this study employs a descriptive quantitative method relying on objective measurements and mathematical analysis to identify user complaints through sentiment analysis using the Long Short-Term Memory (LSTM) machine learning method. The data used consists of 2,000 user reviews of the MyPertamina app obtained from the Google Play Store. The analysis process was conducted using the Python programming language via the Google Colab platform. The results of the study indicate that the majority of user sentiment is negative, suggesting that the quality of MyPertamina's services is still suboptimal. Additionally, this study adopts the five dimensions of e-ServQual to identify factors influencing users' perceptions and sentiment toward the app. These findings are expected to serve as evaluation material for improving MyPertamina's operational services in the future.

Keywords: **s**entiment; user complaints; service quality; e-ServQual.

I. INTRODUCTION

Fossil fuels are strategic commodities that play a vital role in supporting various economic sectors (Marchelia Putri Az Zahra et al., 2024). As a primary energy source, fossil fuels are not only used for transportation, but also for industrial needs, power generation, and households. Dependence on petroleum products makes them a critical component in ensuring the smooth operation of production, distribution of goods and services, and overall economic stability. The price and accessibility of petroleum products significantly impact consumer purchasing power and business operational costs, so their management policies directly affect economic growth, social welfare, and national competitiveness (Dila Lestari, 2022).

According to data from the Integrated Green Business (IEC), Indonesia's energy consumption grows by 7% annually, with the largest distribution in the industrial sector (50%), transportation (34%), households (12%), and commercial (4%). Nearly 95% of this energy demand still comes from fossil fuels (Nurhadi et al., 2024). However, high consumption and dependence on fossil fuels have made Indonesia one of the countries with the largest fossil fuel subsidies in the world. Data from the International Monetary Fund (IMF) shows that in 2023, Indonesia ranked third globally in terms of fossil fuel subsidies, with a total of US$25.74 billion throughout 2022 (www.katadata.co.id). These subsidies consist of gasoline (US$6.69 billion), diesel (US$12.10 billion), kerosene (US$3.09 billion), and other petroleum products (US$3.86 billion).

Although fuel subsidies are intended to help the public, the removal of subsidies that are not targeted at the right people risks causing social and economic instability (Putranta et al., 2023). The Indonesian government notes that the high level of fuel imports is due to increased domestic consumption and surging global oil prices (FItrah et al., 2024). To maintain purchasing power, subsidies remain in place, with the August 2023 allocation reaching Rp61.4 trillion for fuel alone, excluding electricity and LPG subsidies (Chintia Simbolon et al., 2024).

However, the effectiveness of subsidies is questioned because approximately 20-30% of total energy subsidies are enjoyed by groups of people who are not classified as poor (Adi, 2024). The government has formed a Targeted Subsidy Task Force and launched the MyPertamina application to support this policy. This app requires subsidized fuel users to register their vehicles and use a QR code when making purchases (Wardhani et al., 2023). MyPertamina not only functions as a digital payment tool and loyalty program but also as a database to distribute subsidies more accurately.

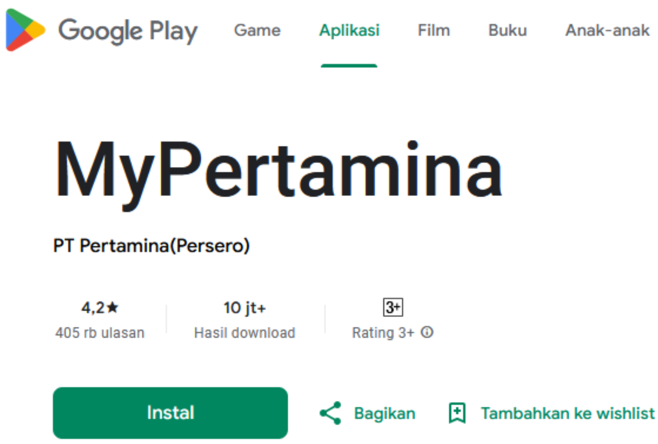

Figure 1 Mypertamina rating on Google Playstore
Source: https://play.google.com

Although it has been downloaded over 10 million times and has a 4.2 rating on the Google Play Store (Indrayanto et al., 2023), user reviews indicate dissatisfaction with the app's performance. Common complaints include difficulties with registration, technical issues, and slow system performance in processing data in real-time. This indicates a gap between expectations and user experience, particularly in terms of digital service quality dimensions such as reliability, efficiency, and ease of access.

Some users even give high ratings but write negative reviews, indicating a discrepancy between scores and user sentiment (Hutabarat et al., 2024). Therefore, sentiment analysis is needed to more accurately identify the problems faced by users. One effective method for this task is Long Short-Term Memory (LSTM), a deep learning algorithm that excels at processing sequential text data (Mutmatimah et al., 2024). Previous research has shown that LSTM has higher accuracy than traditional methods such as Naïve Bayes in sentiment analysis (Isnain et al., 2022).

Based on this background, this study aims to identify the main problems complained about by users of the MyPertamina application, particularly in the context of registering for the Subsidi Tepat program. The results of this analysis are expected to be used as evaluation material to improve the operational quality and service of the MyPertamina application in the future. Therefore, this study is titled: "Analysis of MyPertamina Service Design to Improve Service Quality."

Service Science

Service Science is an interdisciplinary field that combines computer science, engineering, management, and social sciences to study service systems comprehensively. According to (Mobarhantalab 2022), Service Science focuses on the design, delivery, and improvement of services. (Maglio & Spohrer in Revika 2023) define Service Science as the science of service systems aimed at creating more efficient and valuable service innovations.

Electronic Service Quality (e-ServQual)

Electronic Service Quality (e-ServQual) is a method for measuring the quality of electronic services. (Ighomereho, 2022) states that the dimensions of e-Service Quality consist of: (1) Reliability, (2) Responsiveness, (3) Ease of Use, (4) Security/Privacy, and (5) Fulfillment. These five dimensions describe the level of reliability, ease of use, and customer satisfaction in using digital-based services.

Sentiment Analysis

Sentiment analysis is the process of identifying and classifying opinions or emotions in a text. (VARADISA & Kusuma, 2024) states that this analysis is used to determine whether an opinion is positive, negative, or neutral. (Rusli et al. 2020) explains that sentiment analysis is often used in product and service evaluations.

Long Short Term Memory (LSTM)

LSTM is a type of deep learning neural network developed to address the limitations of RNN in remembering long-term information. The LSTM architecture consists of three main gates: (1) Forget Gate, (2) Input Gate, and (3) Output Gate. These three gates control the flow of information within the network, enabling the model to effectively understand long-term temporal dependencies (Turjaman & Budi, 2022).

Confusion Matrix

A confusion matrix is a tool for evaluating the performance of a classification model. Its main components include True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). According to Normawati & Prayogi (2021), metrics such as accuracy, precision, recall, and F1-score are calculated based on this matrix. The Confusion Matrix is important in understanding how well the model predicts the target class (Irwansyah Saputra, 2022).

II. RESEARCH METHODS

The research method used in this study is a descriptive quantitative method, which is an approach that relies on objective measurements and mathematical (statistical) analysis of data samples obtained through questionnaires, polls, tests, or other research instruments to prove or test the proposed hypothesis (Heri Sholehudin, 2024). This study focuses on user reviews and opinions of the MyPertamina app via the Google Play Store as the research object, while the research subjects are individuals who have used the app and provided reviews based on their experiences.

Figure 2 Research Process

In the data analysis process, comprehensive pre-processing steps were carried out, starting with data cleaning, which included case folding, removal of symbols, numbers, emojis, and spaces. Next, text normalization was applied to convert the text into a standard format, followed by sentiment labeling (positive/negative) on each review. The text data is then converted into numerical format through tokenization in preparation for modeling. For model validation, the data is divided into 80% training data and 20% test data, a common

 Volume 09, Number 01, Page 065-071
e-ISSN: 2598-120X; p-ISSN: 2598-117X

practice for optimally forming models and evaluating their generalization capabilities, although this proportion is flexible (Géron, 2019). The primary analysis model used is Long Short-Term Memory (LSTM), a type of Recurrent Neural Network effective for sequential data such as text, and built using the TensorFlow library with the Keras interface.

After training the LSTM model, performance evaluation was conducted using a Confusion Matrix. A Confusion Matrix is a table that provides a visual summary of the classification algorithm's performance, showing how well the model classifies instances from various classes. This matrix enables the calculation of important evaluation metrics such as Accuracy, Precision, Recall, and F1-Score. This Confusion Matrix analysis is crucial for understanding the model's strengths and weaknesses in identifying positive and negative sentiments.

For text visualization and pattern understanding, a Word Cloud was used to identify the most frequently occurring words (Tupari et al., 2023), as well as word network analysis using NodeXL to map the relationships between words in MyPertamina reviews, where words are represented as nodes and their relationships as connecting lines, allowing for the identification of dominant topics and word association patterns in a visual and intuitive manner (Raharjo et al., 2024).

III. RESULT AND DISCUSSION

A. Data Scraping

The data collection process was carried out using web scraping methods on user reviews of the MyPertamina application available on the Google Play Store platform. This technique allows researchers to automatically collect large amounts of data without manual intervention, thereby improving the efficiency and accuracy of the data collection process. The data obtained from the scraping process was 2,132 reviews. There was variation in the ratings that reflected customer satisfaction levels, as follows:

Table 1 Review Characteristics Based on Rating

Rating	Jumlah	Presentase
1	939	46,95%
2	235	11,75%
3	245	12,25%
4	232	11,60%
5	343	17,15%

Source: Primary Data

From this data, there is a significant trend toward negative reviews, which may indicate various factors such as product quality, customer service, or unmet user expectations. The proportion of negative reviews is much higher than positive reviews, indicating that companies or service providers need to evaluate and make improvements to increase customer satisfaction.

B. Preprocessing Text

Table 2 Preprocessing Text

Input	Output
The app is messed up 😟. I filled up with 10 liters, but the filling quota didn't decrease (it's still stuck at the same number as before). People will think it's corruption, but it's not.	The app is acting up. When I fill up the meter, the quota doesn't decrease and remains stagnant at the same number.

Source: Results of Text Pre-processing

After user review data was obtained through web scraping, the next step was to pre-process the text to prepare the data for analysis by the machine learning model. This stage involved several important processes, namely case folding, removal of symbols, numbers, emojis, and spaces. At this stage, the dataset, which originally consisted of 2,132 reviews, was reduced to 1,718 reviews. This reduction in the number of reviews occurred due to the duplicate elimination process, which involves removing reviews with identical content to avoid bias in the analysis, as well as eliminating empty values, where reviews with no content or that do not meet data completeness criteria are removed to prevent them from affecting the analysis results.

The case folding process was carried out by converting all letters to lowercase to standardize word representation, which was found to reduce word variation by 18%. Furthermore, symbols and numbers were removed because they did not contribute meaningfully to the sentiment analysis and were able to simplify the data by 7% of the total initial tokens. Emojis were also removed to maintain the consistency of text-based data and avoid misinterpretation by the model. The removal of double spaces and invisible characters was also carried out to tidy up the text structure and improve the accuracy of the tokenization process.

C. Normalize

Table 3 Normalize Table

Input	Output
I can't register to get a barcode; there's always an error when filling out the form. I've tried it in the morning, afternoon, and evening, but the same thing keeps happening. There's an error when filling out the form, even though everything is correct.	I can not register to get a barcode, there's always an error when filling out the form. I have tried it in the morning, afternoon, and evening, but the same thing keeps happening. There is an error when filling out the form, even though everything is correct.

Source: Normalization Results

In this study, the normalization process was carried out using Google Colab with the Natural Language Toolkit (NLTK) method. These tools were used to detect spelling errors and replace words that did not conform to standard forms. The application of the normalization process to the review data can be seen in the following table, which shows how non-standard words were changed to standard words before further analysis.

D. Labeling

Table 4 Labeling Table

Positif	Negatif
563	1155

Source: Labeling Results

Based on the labeling results, there are a total of 1,718 data points, consisting of 563 positively labeled data points and 1,155 negatively labeled data points. The label distribution shows that there is class imbalance, where negatively labeled data points are almost twice as many as positively labeled data points. This imbalance can affect model performance, especially in terms of accuracy and sensitivity to minority classes (positive).

E. Tokenize

Table 5 Tokenize Table

Input	**Output**
the application is very complicated	[2, 5, 4, 20, 15]
has a list of not detected	[40, 9, 35, 7, 6, 413]
the application is complicated	[2, 5, 4, 15]

Source: Tokenize Results

Tokenization converts text into numerical representations so that it can be processed by the LSTM model. This study uses the Tokenizer from TensorFlow Keras with the parameter num_words=1000 to limit words based on frequency, and oov_token="<OOV>" to handle unknown words. The tokenization results show the mapping of unique words to integer indices.

F. Train-Test Split Validation

Table 6 Train-Test Split Validation Table

Data Training	Data Testing
80%	20%
1374 Data	343 Data

Source: Tokenize Results

The data split process is carried out to divide the dataset into two main parts, namely training data and testing data. In this study, the dataset was divided at a ratio of 80:20, where 80% of the data was used for model training and the remaining 20% was used for testing. The purpose of this division is to objectively evaluate the model's performance on data that has never been seen before.

G. Confussion Matrix

Table 7 Confussion Matrix Table

		Actual Value	
		Positive	Negative
Predicted Value	*Positive*	*True Positive* (94 Data)	*False Negative* (25 Data)
	Negative	*False Positive* (33 Data)	*True Negative* (192 Data)

Source: Confussion Matrix Results

The evaluation of the model using the Confusion Matrix shows that the model successfully classified the data with an accuracy of 83.14%, with 94 True Positives, 192 True Negatives, 33 False Positives, and 25 False Negatives. The precision value of 74.02% reflects the model's ability to avoid false positive predictions, while the recall of 78.99% indicates its effectiveness in recognizing positive data. The specificity of 85.77% indicates reliability in identifying negative data, and the F1-score of 76.38% reflects the balance between precision and recall. Overall, the model demonstrates fairly good sentiment classification performance, although there is room for improvement, particularly with imbalanced data. This reflects the model's balanced performance in identifying positive data while minimizing classification errors. Overall, these results indicate that the model performs fairly well in sentiment classification, although there is room for improvement, especially in the context of imbalanced data.

H. WordCloud

Figure 3 WordCloud
Source : Result WordCloud

An analysis of user reviews of the MyPertamina app shows a significant dominance of negative sentiment, as indicated by the frequency of words such as "complicated," "difficult," "error," "troublesome," "rejected," "bug," "slow," and "fail." These words collectively reflect the numerous user complaints regarding difficulties in using the app, particularly during critical stages such as registration, login, code verification, and barcode usage. Furthermore, the most frequently occurring words, namely "application," "password," "barcode," "vehicle," "register," and "code," indicate that users' primary focus is on technical issues and an unsatisfactory user experience (UX). Although there are some positive-toned words like "good," "helpful," and "stable," their occurrence is far less frequent compared to negative words. Overall, the reviews also highlight

Volume 09, Number 01, Page 065-071
e-ISSN: 2598-120X; p-ISSN: 2598-117X

issues with security and login systems, an unintuitive user experience, and operational challenges such as errors and system rejections, all of which contribute to the negative perception of the app.

I. Word Network Visualization

Figure 4 Word Network Visualization
Source : Result Word Network Visualization (NodeXl)

The results of the word network visualization show that the application node has the largest size and the highest degree of connectivity, indicating that the main topic in the text corpus centers on the use of applications. The connectivity of application with words such as password, time, and code reflects users' focus on technical issues and system security aspects. Additionally, the appearance of nodes such as "complicated," "difficult," and "make" indicates perceptions of complexity in application usage, particularly regarding login or verification processes, as reinforced by the connection between the words 'time' and "enter." On the other hand, words like "gas," "company," and "companies" appear in the same community, indicating discussions related to the energy industry sector, although the intensity of this topic is not as high as issues related to the application itself. Security aspects also stand out through the connection between 'application' and words like "barcode," "code," and "send," which reflect users' attention to code-based authentication systems or scanning as part of the verification process within the application.

Table 8 result Dimension of e-ServQual

Dimension of e-ServQual	Output
Reliability	Failed login and OTP not received
Responsiveness	Slow response to complaints
Ease of use	Application not user-friendly
Security	Lack of trust in the system
Fulfilment	Users feel misunderstood

Analysis based on the e-ServQual dimensions shows that the quality of the MyPertamina application service still faces various challenges. In terms of reliability, many users fail to log in due to OTPs not being received, reflecting the unreliability of the system. In terms of responsiveness, user complaints are not responded to quickly, indicating weak technical support. The ease of use dimension is hampered by a user-unfriendly interface, with complaints such as "complicated" being dominant. In terms of security, technical failures undermine trust in the digital system. Meanwhile, the fulfilment aspect has not shown empathy for the diverse needs and conditions of users, creating the impression that the application is more policy-oriented than user-friendly.

Based on the analysis results, it can be concluded that after the launch of the digital application, improving the quality of electronic services (E-ServQual) is key to maintaining user satisfaction. The five main dimensions of E-ServQual—reliability, responsiveness, ease of use, security, and fulfillment—play an important role in shaping users' perceptions of service quality. In the context of the Industrial Revolution 5.0, where personalization and smart technology are increasingly dominant, digital service providers are required to be adaptive and responsive to user needs and feedback.

An analysis of the MyPertamina app reveals several areas that require improvement to achieve optimal user satisfaction, including:

1) Service Reputation through Positive Testimonials

Service reputation can be strengthened through the use of electronic word of mouth (e-WOM) and user testimonials as forms of social proof. User trust in testimonials significantly influences initial perceptions of app quality. This concept is reinforced by research conducted by (Anshori, 2024) on the theory of Electronic Word of Mouth (e-WOM), which is the dissemination of information from one consumer to another through digital media (such as comments on social media, app reviews, or online forums). This theory states that positive reviews from previous users can greatly influence the perceptions and decisions of other potential users, as they are considered more objective and trustworthy than formal advertisements.

2) Utilization of Artificial Intelligence (AI)

AI plays a strategic role in operational efficiency and user feedback data analysis. This technology enables process automation, identification of user preference trends, and enhanced data-driven service personalization. According to (Siagian & Rony, 2024) Artificial Intelligence (AI) plays a strategic role in improving the efficiency and productivity of operational management through process automation, accelerated data processing, and supply chain optimization.

3) Real-Time Notifications and Feedback

Implementing a clear and responsive feedback system in the app helps improve the user experience and reduce confusion when technical issues arise. User-centered design principles are essential for creating informative and efficient interactions. This is also in line with research conducted by (Chandra et al., 2024). Increased customer satisfaction can be achieved through quick and professional complaint handling.

4) Enhancing Service Staff Capacity

Technical and interpersonal training for service staff is a key component in ensuring quick, empathetic, and solution-oriented responses to user needs or complaints. Human resource competencies also strengthen overall service quality. In this context, staff play a strategic role as

Volume 09, Number 01, Page 065-071
e-ISSN: 2598-120X; p-ISSN: 2598-117X

the primary controllers in directing and managing the company's development process through their highly competent skills (Admanegara & Handayani, 2024).

Overall, a sustainable approach to improving technology-based service quality—both from the system and human resource perspectives—is crucial for maintaining user loyalty and the competitiveness of digital applications in the era of industrial transformation.

IV. CONCLUSIONS

Based on the results of the LSTM model analysis and evaluation, it can be concluded that the quality of the MyPertamina application service is still considered suboptimal, with the majority of reviews being negative, indicating problems in the e-ServQual dimensions such as login system reliability, responsiveness to complaints, ease of use, security, and fulfillment of user needs. Although the model demonstrates satisfactory performance, data imbalance leads to a decrease in accuracy in classifying positive sentiment. Therefore, it is recommended to perform data balancing using techniques such as SMOTE and conduct a deeper analysis of classification errors to improve model accuracy and support more precise managerial decision-making in the development of public digital services.

REFERENCES

[1] Adi, A. C. (2024). Fokus Benahi Subsidi Tepat Sasaran, Pemerintah Kaji Beberapa Opsi Skema Penyaluran. Kementerian Energi Dan Sumber Daya Mineral Republik Indonesia. Https://Www.Esdm.Go.Id/Id/Media-Center/Arsip-Berita/Fokus-Benahi-Subsidi-Tepat-Sasaran-Pemerintah-Kaji-Beberapa-Opsi-Skema-Penyaluran

[2] Chintia Simbolon, I., Karolina Sidebang, L., Theofani Margaret, N., Valencia Pangaribuan, S., & Kemala Dewi Lubi, P. (2024). Analisis Dampak Kebijakan Perubahan Publik Harga Bbm Terhadap Perekonomian Rakyat Indonesia. El-Mal: Jurnal Kajian Ekonomi & Bisnis Islam, 5(4), 2519–2528. Https://Doi.Org/10.47467/Elmal.V5i4.1112

[3] Dila Lestari, F. (2022). Kenaikan Harga Bbm Dan Pengaruhnya Terhadap Tingkat Inflasi Di Indonesia. Journal Of Islamic Business Management Studies, 3(2), 87–96.

[4] Fitrah, H., Marliyah, & Rahmani, N. A. B. (2024). Analisis Elektrifikasi Transportasi Untuk Penghematan Subsidi Bbm. Jurnal Ilmiah Ekonomi Islam, 10(02), 2371–2383.

[5] Hutabarat, A. W. V., Adnyani, N. L. S. S., & Suryadi, K. (2024). Analisis Sentimen Data Ulasan Pengguna Mypertamina Di Twitter Dengan Metode Text Mining. Jurnal Rekayasa Sistem Industri, 13(1), 145–154. Https://Doi.Org/10.26593/Jrsi.V13i1.6958.145-154

[6] Harahap, N. K. (2021). Analisis Kelangkaan Bbm Premium Di Padangsidimpuan Perspektif Hukum Positif Dan Hukum Ekonomi Syariah. Yurisprudentia: Jurnal Hukum Ekonomi, 7(1), 56–76.

[7] Hutabarat, A. W. V., Adnyani, N. L. S. S., & Suryadi, K. (2024). Analisis Sentimen Data Ulasan Pengguna Mypertamina Di Twitter Dengan Metode Text Mining. Jurnal Rekayasa Sistem Industri, 13(1), 145–154. Https://Doi.Org/10.26593/Jrsi.V13i1.6958.145-154

[8] Ighomereho, O. S. (2022). Impact Of E-Service Quality On Customer Satisfaction: A Study Of Internet Banking For General And Maritime Services In Nigeria. 28(3), 488–501. Https://Doi.Org/10.1057/S41264-022-00164-X

[9] Isnain, A. R., Sulistiani, H., Hurohman, B. M., Nurkholis, A., & Styawati, S. (2022). Analisis Perbandingan Algoritma Lstm Dan Naive Bayes Untuk Analisis Sentimen. Jurnal Edukasi Dan Penelitian Informatika (Jepin), 8(2), 299. Https://Doi.Org/10.26418/Jp.V8i2.54704

[10] Indrayanto, C. G., Ratnawati, D. E., & Rahayudi, B. (2023). Analisis Sentimen Data Ulasan Pengguna Aplikasi Mypertamina Di Indonesia Pada Google Play Store Menggunakan Metode Random Forest. Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer, 7(3), 1131–1139. Http://J-Ptiik.Ub.Ac.Id

[11] Kumalasari, A. T., & Handayani, W. (2024). Sentiment Analysis To Improve The Quality Of Public Transportation Services "Suroboyo Bus." Indonesian Interdisciplinary Journal Of Sharia Economics (Iijse), 7(3), 6407–6426.

[12] Marchelia Putri Az Zahra, N., Runtu Leluni, I., Nafisah, I., Choiron Nur Rizqi, A., Khoiriawati, N., Sayyid Ali Rahmatullah Tulungagung Alamat, U., Mayor Sujadi No, J., Kedungwaru, K., Tulungagung, K., & Timur, J. (2024). Pengaruh Kenaikan Harga Bbm Subsidi Terhadap Pengeluaran Konsumsi Rumah Tangga Di Kabupaten Tulungagung. 2(3), 46–57. Https://Doi.Org/10.61132/Santri.V2i3.564

[13] Mutmatimah, S., Khairunnas, & Khairunnisa. (2024). Metode Deep Learning Lstm Dalam Analisis Sentimen Aplikasi Pedulilindungi. Journal Of Computers Sciences And Informatics, 1(1), 9–19. Https://Doi.Org/10.34304/Scientific.V1i1.231

[14] Othman, B., Weijun, H., Huang, Z., Xi, J., & Ramsey, T. (2020). Effect Of Service Quality On Service Value And Customer Retention For Clothing Store Brands In China. Tekstilec, 63(4), 242–255. Https://Doi.Org/10.14502/Tekstilec2020.64.242-255

[15] Pramudya, E., Pradana, Tri Nugraha, J., Mukti, A., & Widyantoro, S. (2024). Analisis Service Quality Dengan Metode Csi Dan Ipa Terhadap Kepuasan Peserta. Innovative: Journal Of Social Science Research, 4, 1–15.

[16] Putranta, Y. S. V., Rahayudi, B., & Purnomo, W. (2023). Analisis Sentimen Masyarakat Terhadap Kebijakan Penghapusan Subsidibbm Pada Media Sosial Twitter Menggunakan Algoritma Naive Bayesclassifier Dengan Ekstraksi Fitur N-Gram Tf-Idf. Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer, 7(3), 1501–1510. Http://J-Ptiik.Ub.Ac.Id

[17] Sukma Rukmana, & Wiwik Handayani. (2023). Analysis Of Service Science Design Through Customer Experience To Increase Posaja Application User Satisfaction. Kontigensi : Jurnal Ilmiah Manajemen, 11(2), 513–527. Https://Doi.Org/10.56457/Jimk.V11i2.402
[18] Turjaman, R. M., & Budi, I. (2022). Analisis Sentimen Berbasis Aspek Marketing Mix Terhadap Ulasan Aplikasi Dompet Digital (Studi Kasus: Aplikasi Linkaja Pada Twitter). Jurnal Darma Agung, 30(2), 266. Https://Doi.Org/10.46930/Ojsuda.V30i2.1672
[19] Varadisa, A. Q., & Kusuma, Y. B. (2024). Implementasi Marketing Mix Dalam Meningkatkan Brand Image.
[20] Wardhani, P. A., Luqman, Y., & Noor, W. (2023). Sikap Media Detik.Com Terhadap Kebijakan Subsidi Tepat Sasaran Mypertamina. Interaksi Online, 11(4), 61–72.