DIJEFA: Dinasti International Journal of Economics, Finance & Accounting
E-ISSN: 2721-303X
P-ISSN: 2721-3021
https://dinastipub.org/DIJEFA dinasti.info@gmail.com +62 811 7404 455

DOI: https://doi.org/10.38035/dijefa.v6i5.5176
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Received: 12 July 2025 | **Revised:** 21 September 2025 | **Accepted:** 05 October 2025

M-Health Service Quality Analysis of Kimia Farma Mobile Application on Google Play Store Using Sentiment Analysis and Topic Modeling Methods

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Abstract: Digital Transformation in the pharmaceutical industry grew rapidly, accelerated by the COVID-19 pandemic, leading to a surge in mobile healthcare service transactions. Kimia Farma Mobile, initiated by PT Kimia Farma Apotek, is a m-health application that provided medicine purchase, consultation, and laboratory services. However, the Kimia Farma Mobile application had a lower rating than its competitors. This study aimed to analyze user satisfaction and dissatisfaction levels based on Google Play Store reviews to understand the root causes of its low rating. Utilizing sentiment analysis, reviews were classified into positive and negative polarities. Latent Dirichlet Allocation (LDA) was then used to identify key factors influencing satisfaction and dissatisfaction within the M-Health Service Quality framework. The Support Vector Machine (SVM) method was chosen for its high accuracy, yielding an F1-score of 97.39%. The results showed that positive reviews were primarily driven by ease of use and helped users in providing optimal services. In contrast, negative reviews were linked to issues in Information Quality, Interaction Quality, and System Quality. This study concludes by providing specific recommendations to improve the application's service quality, operational systems, and overall user experience to enhance satisfaction and boost its rating.

Keywords: User Satisfaction, Digital Health, KNN, SVM, LDA, M-Health Service Quality, Kimia Farma Mobile.

INTRODUCTION

The digital transformation of Indonesia's pharmaceutical sector has undergone a significant acceleration, especially since the COVID-19 pandemic drove a change in consumer behavior toward application-based healthcare services. This phenomenon creates both opportunities and challenges for pharmaceutical companies to adapt (Mubarok, 2017). As one of the largest state-owned pharmaceutical companies, PT Kimia Farma, Tbk., responded by launching the Kimia Farma Mobile application. However, despite its strong market position, the application has only received an average rating of 3.6 out of 5 on the Google Play Store,

significantly below its competitors. This low level of user satisfaction indicates a fundamental problem that requires in-depth analysis.

Studies on Electronic Word of Mouth (EWOM) have shown that online reviews possess high credibility and significantly influence consumer purchasing decisions (Rosario et al., 2016). Nevertheless, a significant gap still exists in the literature, particularly concerning the comprehensive evaluation of the service quality of healthcare applications within the Indonesian context. Manually analyzing thousands of user reviews is a challenging and time-consuming process (Kumar et al., 2023). Few studies have specifically applied automated approaches, such as sentiment analysis and topic modeling, to user reviews of a local healthcare application to identify the root causes of dissatisfaction. Wulandari & Hidayanto (2023) analyzed the service quality of the PeduliLindungi application using sentiment analysis and topic modeling. However, no previous research has analyzed pharmaceutical apps. Therefore, this research aims to fill this gap by systematically and automatically leveraging Kimia Farma Mobile's user review data, which allows for the structured and measurable identification of problems. The goal of this study is to analyze user satisfaction and dissatisfaction levels, identify the key determinants, and propose actionable recommendations for improvement.

This research selects Kimia Farma Mobile as its object of study due to its position as an application initiated by a state-owned pharmaceutical company. The low rating of this application, despite being backed by the company's prominent name, reflects crucial strategic and operational issues. The analysis of this application will not only provide valuable insights for the developers at Kimia Farma Apotek for direct improvement but can also serve as a benchmark for other healthcare applications in Indonesia that seek to enhance their service quality. By analyzing user reviews through the m-health service quality framework (Akter et al., 2013), this study can identify the specific factors influencing satisfaction and dissatisfaction, thereby formulating targeted recommendations.

METHODS

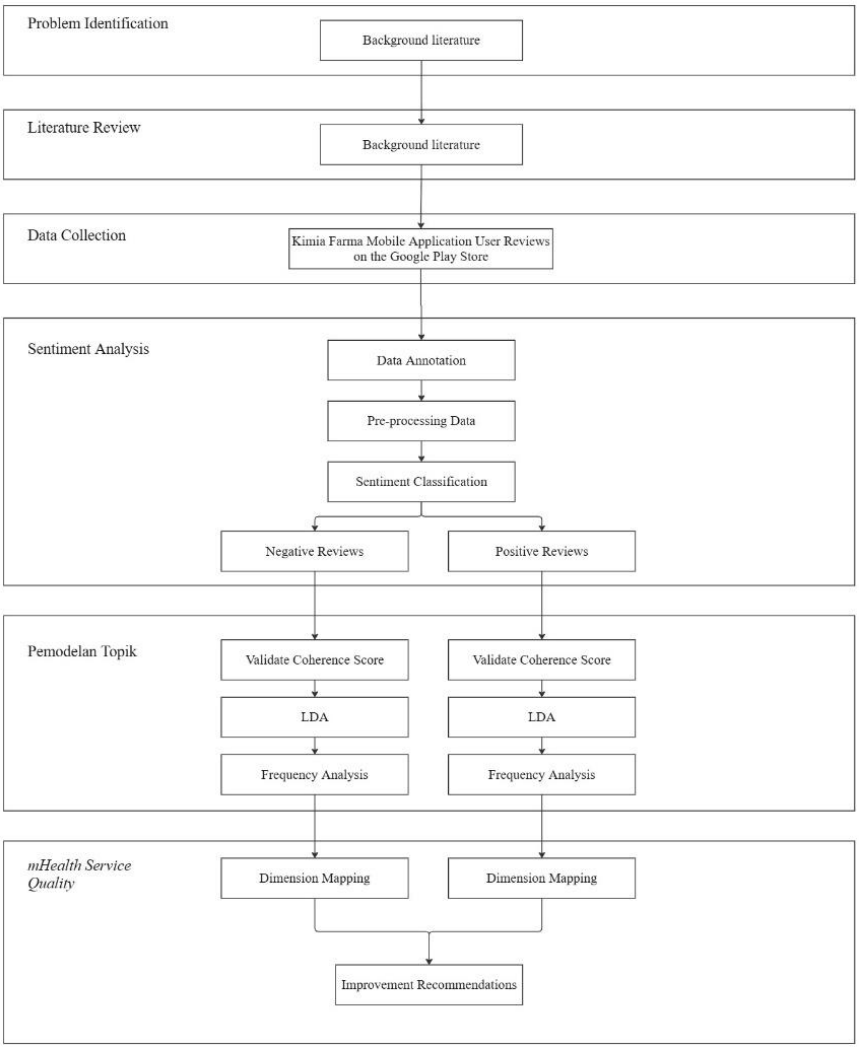
The research stages in Figure 2 are conducted to answer all the research questions. The output of this research is a recommendation to improve the quality of the Kimia Farma Mobile application, thereby enhancing the service quality provided to users.

The initial problem identification section forms the basis of the research on the Kimia Farma Mobile application. The problems are revealed through a comparison between the expected conditions and the reality in the field. The expectation is that the application can improve service quality and user satisfaction; however, the application receives a low rating on the Google Play Store, indicating low user satisfaction. Furthermore, user reviews have not yet been reviewed systematically and have not been utilized as a basis for service development. The application's rating is also still relatively low when compared to similar applications. Based on these conditions, this research will answer three main questions: what is the level of user satisfaction and dissatisfaction from reviews on the Google Play Store through sentiment analysis; what are the determining factors that influence user satisfaction and dissatisfaction based on the Mobile Health Service Quality dimensions through topic modeling; and how to formulate application improvement recommendations based on the results of this analysis.

The literature review is compiled to support the entire research process based on the formulated questions and objectives. In this section, the theoretical framework is established as the foundation for the research flow, which includes the scope, methods, evaluation, review of previous research, and the conceptual framework that leads to answers to the research questions.

The object of the research is the Kimia Farma Mobile application, an omnichannel in the digital health sector developed by PT Kimia Farma Apotek since 2020. Review data was collected through web scraping techniques using google-play-scraper library in the Python

programming language. This process used the application ID obtained from the application's URL on the Google Play Store.



Figure~~Gambar~~ 2
~~Tahapan Penelitian~~Research Stages

Sample data is created for sentiment analysis training using the Slovin's formula, which is commonly used in statistics for large populations. Slovin's formula is used because, in this study, the population is large and its size is known with certainty. The formula is:

$$n = \frac{N}{1+Ne^2} \quad \text{.....1}$$

~~n=N/(1+Ne²n).....1~~

N is the population size, and e is the margin of error, and n is the sample size. After that, the data is manually annotated by the researcher. Reviews are considered positive or negative if they have characteristics of positive/negative connotations, positive/negative suggestions, expectations with positive/negative connotations, encouraging words that depict optimistic/pessimistic sentiment, or action words that depict optimistic/pessimistic sentiment.

The pre-processing data stages for sentiment analysis include case folding to convert all characters to lowercase, tokenization to break down into individual tokens such as words or

phrases, stemming to reduce words to their base form, stopword removal to eliminate words that do not have meaning, and normalization to standardize text forms to be consistent and uniform, so that the text data is optimally used for the subsequent machine learning process in sentiment classification (Garini et al., 2023; Ibtissam et al., 2023; Kusumawati et al., 2019). The stopword file and stemmer are obtained from previous research conducted by Mustaqim et al. (2024).

Sentiment analysis is performed using the K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) algorithms, which are chosen based on their superior performance (Atmadja et al., 2019; Sahu & Ahuja, 2016). K-Nearest Neighbors (KNN) is widely used in text classification due to two main advantages: its simplicity and its ability to achieve an error rate equivalent to that of far more complex methods. In fact, KNN can often match or even outperform more sophisticated methods in terms of generalization error (Garcia-Pedrajas et al., 2017). Several previous studies have concluded that Support Vector Machine (SVM) has superior accuracy compared to other classification methods (Firmansyah & Asnawi, 2019; Kusumawati et al., 2019; Oduntan et al., 2022; Pradha et al., 2019). SVM is a dominant algorithm in the field of sentiment classification. Previous research has used SVM for classification purposes, and in most cases, this technique has yielded the best performance (Ligthart et al., 2021). The performance of the models is evaluated using metrics such as accuracy, precision, recall, and F1-score through 10-fold cross-validation (Birjali et al., 2021). Generally, a model is accepted when the F1-score is higher than 70% (Leem & Eum, 2021). Miric & Huang (2023) explain that 10-fold cross-validation is conducted by repeating the classification ten times. The data is randomly divided into ten parts (folds), and each part is used as validation data alternately. This method ensures that the selection of training data does not affect the overall performance of the model.

After the classification of positive and negative review polarities, topic modeling is operated using the Latent Dirichlet Allocation (LDA) method developed by Blei et al. (2015). LDA is an unsupervised machine learning algorithm widely used in text processing to identify hidden topics based on the distribution of words in documents (Çallı, 2023). This process is conducted with the Python Gensim library, and the optimal number of topics is determined based on the coherence score, where the higher the value, the more relevant and cohesive the formed topics (Abdelrazek et al., 2023).

Each topic generated by LDA, in the form of a collection of 10 main words, is then mapped to the dimensions and sub-dimensions of the M-Health Service Quality framework, namely System Quality (reliability, privacy, efficiency), Interaction Quality (cooperation, confidence, care), and Information Quality (utilitarian & hedonic) (Akter et al., 2013). The mapping process is carried out by researchers and experts. They review the topic modeling results and the classified reviews while also referring to the definition of each dimension to maintain the objectivity of the classification (Palese & Usai, 2018).

From the mapping results of each positive and negative topic that has been mapped into M-Health Service Quality, the research proceeds with providing concrete contributions to the improvement of digital service design, as well as the development of a more precise and user-centric user feedback-based recommendation system.

RESULTS AND DISCUSSION

PData Collection~~engumpulan Data~~

This study focused on user reviews of the Kimia Farma Mobile application from the Google Play Store, as its rating on the App Store was deemed satisfactory. Review Collected up to September 29, 2024, using web scraping techniques. This technique utilized an open-source library to extract data from websites (Birjali et al., 2021). The process of retrieving reviews was done with the Google Play Scraper library, using the review_all function which

employed the Kimia Farma Mobile application ID, com.kimiafarma.online. The total reviews collected was 11,144 reviews. This research focuses on user reviews of the Kimia Farma Mobile application on the Google Play Store because the rating on the App Store is already quite good.

~~Penentuan Ukuran Sample~~Sample Size Determination

This research used the Slovin's method to determine the sample size from the total of 11,144 reviews of the Kimia Farma Mobile application on the Google Play Store. With an error rate of 2.5%, which was smaller than the standard 5-10% for better population representation, a sample of 1,399 reviews was obtained.

This sample size was equivalent to 12.56% of the total reviews. To ensure adequate population representation, the researchers rounded the sample up to 15%, which was 1,672 reviews. This rounding was done to obtain a sufficiently representative sample. The 15% sample was selected randomly using Google Colab as training data.

~~Analisis Sentimen~~ Sentiment Analysis

1. ~~Anotasi~~ Data Annotation

   The training data of 1,672 reviews were then manually labeled as positive or negative by the researchers, following annotation guidelines designed to ensure labeling uniformity (Uliniansyah et al., 2024). The labeling results showed that out of 1,672 reviews, 1,575 were labeled positive and 97 were labeled negative.
2. ~~Pra Pemrosesan Data~~Pre-processing Data

   Pre-processing data was an essential step in text analysis, which aimed to clean and prepare the review data before further analysis. This stage consisted of four main steps: case folding, tokenization, stemming, and stop word removal, which were implemented using RapidMiner.

   a. Case Folding aimed to eliminate feature duplication due to differences in capitalization. For example, “VERY HELPFUL AND VERY NEEDED FOR THE CURRENT SITUATION” was changed to “very helpful and very needed for the current situation”.
   b. Tokenization in this research used the “non letters” mode to separate tokens based on characters other than letters, such as punctuation and emojis. For example, the review “very helpful and very needed for the current situation” was changed to “very”, “helpful”, “and”, “very”, “needed”, “for”, “the”, “current”, “situation”.
   c. Stemming in this research used an Indonesian stemming dictionary adapted to the context of Kimia Farma Mobile application reviews. For example, “helpful” was changed to “help”.
   ~~a.~~d. Stop Word Removal aimed to increase computational efficiency and accelerate analysis by focusing on important words. For example, “very helpful and very needed for the current situation” was changed to “very help very need situation”.
3. ~~Algoritma~~ K-Nearest Neighbors (KNN) Algorithm

   This research used the KNN algorithm for sentiment analysis, with a k-value of 11 as the parameter in the training domain. This process involved applying the KNN model, which was then evaluated using the Apply Model and Performance operators in the testing domain in RapidMiner.

   The research results showed that the KNN model achieved an accuracy of 93.86%, precision of 94.46%, and an F1-Score of 96.80%. From the data of 11,144 reviews to which the KNN algorithm was applied, it was found to produce 10,966 positive reviews and 178 negative reviews.
4. ~~Algoritma~~ Support Vector Machine (SVM) Algorithm

The first step was to use the "Classification by Regression" operator in the training domain. The SVM operator was then applied with default parameter modes such as kernel type, kernel cache, and C. This process was followed by applying the model using the "Apply Model" operator and evaluating performance using the "Performance" operator in the testing domain.

The research results showed that the SVM model achieved an accuracy of 95.00%, precision of 95.21%, and an F1-Score of 97.39%. From a total of 11,144 reviews, the SVM algorithm classified 10,878 reviews as positive and 266 reviews as negative.

5. ~~Pembahasan Analisis Sentimen~~Sentiment Analysis Discussion

The F1-Score comparison results between the SVM and KNN algorithms showed that SVM had the best performance with an F1-Score of 97.39%. From the analysis using SVM, the sentiment classification results obtained were 10,878 reviews (97.61%) classified as positive, indicating user satisfaction, and 266 reviews (2.39%) classified as negative, reflecting dissatisfaction. This stage answered the level of user satisfaction and dissatisfaction with the Kimia Farma Mobile application from reviews on the Google Play Store, which showed that most user reviews for the Kimia Farma Mobile application were positive and satisfied. This was in line with the current application rating score of 3.6, which was closer to a rating of 5 than a rating of 1. However, there was still room for improvement, especially by understanding customer perceptions through their reviews. Therefore, this research then continued by identifying the determining factors of user satisfaction and dissatisfaction based on the Mobile Health Service Quality dimensions, using topic modeling.

~~Pemodelan Topik~~Topic Modeling

The preceding sentiment analysis yielded the SVM algorithm with an F1-Score of 97.39%, which was used to separate positive and negative reviews. These two groups of reviews were then analyzed separately using topic modeling to understand the factors that influenced user satisfaction and dissatisfaction.

1. Positive Reviews~~Ulasan Positif~~

This research analyzed 10,878 positive reviews (97.61% of the total reviews) using LDA topic modeling to understand the factors that influenced user satisfaction with the Kimia Farma Mobile application. The first step was to determine the optimal number of topics using the coherence score, which resulted in 5 topics as the optimal number based on the highest coherence value of 0.5309, as shown in Figure 3. Each topic was represented by 10 keywords, which can be seen in Table 2.

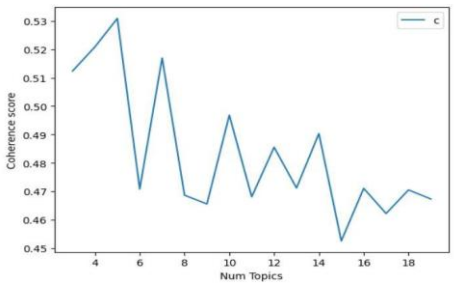


Figure 3. Positive Coherence Score

Table 2. Topic Modeling Results for Positive Kimia Farma Mobile Reviews

Topic Number	Keyword	Frequency
1	Medicine, application, help, search, vitamin, easy, mask, pandemic, buy, simple	38.54%
2	Kimia, Farma, medicine, easy, application, mobile, help, home, buy, pandemic	26.30%
3	Fast, free, shipping, discount, price, great, direct, application, send, home	14.94%

Topic Number	Keyword	Frequency
4	Good, application, help, swab, easy, benefit, PCR, reservation, direct, complicated	13.83%

2. Topik 1 sebesar 38,54% menghasilkan kata kunci obat, aplikasi, bantu, cari, vitamin, mudah, masker, pandemi, beli, gampang. Topik 2 sebesar 26,30% menghasilkan kata kunci kimia, farma, obat, mudah, aplikasi, *mobile*, bantu, rumah, beli, pandemi. Topik 3 sebesar 14,94% menghasilkan kata kunci cepat, gratis, ongkir, diskon, harga, mantap, langsung, aplikasi, kirim, rumah. Topik 4 sebesar 13,83% menghasilkan kata kunci bagus, aplikasi, bantu, swab, mudah, manfaat, per, reservasi, langsung, ribet. Topik 5 sebesar 6,40% menghasilkan kata kunci layanan, aplikasi, solusi, lengkap, kirim, bayar, pesan, barang, jam, habis.

3.2. Ulasan Negative Reviews

This research analyzed 266 negative reviews (2.39% of the total reviews) using topic modeling (LDA) to identify the factors that influenced user dissatisfaction with the Kimia Farma Mobile application. The first step was to determine the optimal number of topics using the coherence score, which resulted in 5 topics as the optimal number based on the highest coherence value of 0.4193, as shown in Figure 4. Each topic was represented by 10 keywords, which can be seen in Table 3.

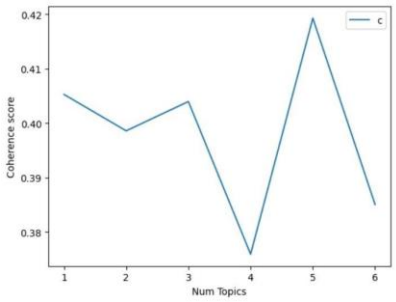


Figure 4. Negative Coherence Score

Table 3. Topic Modeling Results for Negative Kimia Farma Mobile Reviews

Topic Number	Keyword	Frequency
1	OTP, application, email, code, enter, register, send, verification, login, please	54.89%
2	Medicine, application, pay, stock, goods, pick up, out of stock, kimia, price, pharmacy	13.53%
3	Application, farma, kimia, send, buy, pay, medicine, outlet, use, online	11.65%
4	Application, voucher, use, service, process, vaccine, please, lost, medicine, send	10.90%
5	Medicine, order, cancel, hours, pay, order, send, driver, goods, please	9.02%

Topik 1 sebesar 54,89% menghasilkan kata kunci otp, aplikasi, email, kode, masuk, daftar, kirim, verifikasi, login, tolong. Topik 2 sebesar 13,53% menghasilkan kata kunci obat, aplikasi, bayar, stok, barang, ambil, habis, kimia, harga, apotek. Topik 3 sebesar 11,65% menghasilkan kata kunci aplikasi, farma, kimia, kirim, beli, bayar, obat, outlet, pakai, online. Topik 4 sebesar 10,90% menghasilkan kata kunci aplikasi, voucher, pakai, layan, proses, vaksin, tolong, hilang, obat, kirim. Topik 5 sebesar 9,02% menghasilkan kata kunci obat, pesan, cancel, jam, bayar, order, kirim, driver, barang, tolong.

Pemetaan Topik Topic Mapping

The positive and negative topics identified were subsequently mapped onto the m-health service quality framework. This mapping process was conducted by the researchers in consultation with an expert possessing extensive knowledge and experience in information technology and digital application development and maintenance. The alignment was achieved through an analysis of the keywords and illustrative reviews associated with each topic, which were then correlated with the definitions of the respective domains within the m-Health Service Quality framework. The results of this mapping of each Latent Dirichlet Allocation (LDA) topic derived from positive and negative reviews are presented in the subsequent table.

Tabele 2. Hasil Pemetaan Topik LDA dalam Dimensi *M-Health Service Quality*Mapping of LDA Topics within M-Health Service Quality Dimensions

Ulasan Positivef Review				Ulasan Negative Reviewf			
No TopikTopic Number	Dimension	Service Quality	Persentage ase	Topic Number No Topik	DimensionDimensi	Service Quality*Service Quality*	PersentagePersentase
1	Information QualityKualitas Informasi	UtilitarianManfaat Utilitarian	64,84%	1	Information QualityKualitas Informasi	Manfaat Utilitarian	54,89%
2		Manfaat Utilitarian		2	Interaction QualityKualitas Interaksi	CooperationKerjasama	25,18%
3	System QualityKualitas Sistem	System EfficiencyEfisiensi Sistem	14,94%	3		CooperationKerjasama	
4	Interaction QualityKualitas Interaksi	CooperationKerjasama	20,23	4	System QualityKualitas Sistem	System ReliabilityKeandalan Sistem	19,92%
5		CareKepedulian		5		System ReliabilityKeandalan Sistem	

This section answered the determining factors that influenced user satisfaction and dissatisfaction based on the Mobile Health Service Quality dimensions. The m-health service quality framework developed by Akter et al. (2013) was used as the basis for the analysis, which comprised three main dimensions: system quality, interaction quality, and information quality, where each dimension is mapped to the topics generated by the LDA method. This mapping is accompanied by the frequency of each topic, presented as a review count or a percentage.

This process yielded a list of service quality dimensions in positive reviews consisting of: Information Quality - Utilitarian, Information Quality - Utilitarian, System Quality - System Efficiency, Interaction Quality – Cooperation, Interaction Quality – Care. From the positive reviews given by users, it provided the conclusion that information quality in utilitarian benefits, system quality in system efficiency, and interaction quality in cooperation and care were considered factors of user satisfaction in using the Kimia Farma Mobile application to continue using the application and could have an impact on increasing sales turnover for the Company as well as increasing the application rating. This could be considered a strength possessed by the Kimia Farma Mobile application to always provide continuous improvement.

In addition, this process yielded a list of service quality dimensions in negative reviews consisting of: Information Quality - Utilitarian, Interaction Quality - Cooperation, Interaction Quality - Cooperation, System Quality – System Reliability, System Quality – System Reliability. From the negative reviews given by users, it provided the conclusion that information quality in utilitarian, interaction quality in cooperation, and system quality in system reliability were considered factors of user dissatisfaction in using the Kimia Farma Mobile application that needed to be fixed or improved immediately. This was a risk that still posed a threat to the Kimia Farma Mobile application and could serve as a basis for improvements and enhancements for application developers to retain users, increase company turnover, and impact rating improvement.

Akter et al. (2013) emphasized that the service quality construct they developed was very relevant for decision-makers in the m-health platform because it reflected how customers evaluated services not only overall but also at the dimension and sub-dimension levels. This construct provided strategic guidance for managers to improve service quality. Furthermore,

Akter et al. also stated that service quality dimensions interacted in influencing user satisfaction and sustainability intention. By making service quality a strategic goal, m-health providers could not only increase organizational loyalty and revenue but also contribute to better health outcomes and an improved quality of life for the community.

~~Rekomendasi Perbaikan Aplikasi Kimia Farma Mobile~~Recommendations for Improving the Kimia Farma Mobile Application

The main problem in this research lay in the negative reviews that reflected user dissatisfaction with the Kimia Farma Mobile application and answered the question regarding recommendations for application improvement. This dissatisfaction became a significant challenge that needed to be addressed immediately to encourage sustainable application development.

Based on the Mobile Health Service Quality framework and identified through topic modeling and its reviews, the Information Quality – Utilitarian dimension dominated with a proportion of 54.89%, indicating that there were still technical issues such as bugs, especially in the account registration process, OTP code validation, and application login. Common complaints included system failures in detecting already registered user numbers and limited information provided through official channels such as FAQs or direct messages. Other problems arose from the Interaction Quality – Cooperation dimensions at 13.53% and 11.65%, which highlighted issues related to inventory and payment processes. Users reported discrepancies in product stock in the application and unilateral transaction cancellation without a clear refund system. The lack of integration and coordination between the application and Kimia Farma outlets lengthened the customer journey, especially in resolving failed or incomplete transactions. On the system side, two other negative review topics with percentages of 10.90% and 9.02% respectively, highlighted problems with the voucher system, order cancellations, and item delivery. These complaints demonstrated the weakness of the system's reliability in consistently and responsively supporting services.

As a solution, this research recommended information improvements with the development of a more informative FAQ feature, the addition of a validation system and automatic logic to handle OTP requests, and Quality Assurance optimization to find parts of the application that needed fixing. Interaction improvements included the establishment of an integrated stock center with dedicated personnel (PIC), optimization of the call center function, and the implementation of a 24-hour customer service chatbot to increase responsiveness, as well as simplifying the customer journey. System improvements related to payment integration and automatic refund procedures were also suggested to reduce obstacles in the transaction process; adjusting the application system algorithm could automatically return vouchers when transactions failed. By implementing these findings-based improvements, the Kimia Farma Mobile application was expected to increase user satisfaction, expand the customer base, improve ratings, and have a positive impact on the company's overall business performance.

CONCLUSION

This research enriched the literature on digital service quality evaluation in the context of mobile-based health applications, particularly by adopting a sentiment analysis and LDA-based topic modeling approach. The research findings indicated that most users expressed satisfaction with the Kimia Farma Mobile application, with 97.61% of reviews being positive and only 2.39% being negative. This affirmed the importance of m-health service quality dimensions in creating a positive and sustainable user experience.

Furthermore, through topic mapping linked to the M-Health Service Quality dimensions, this research successfully identified key factors influencing user satisfaction and dissatisfaction. Factors that contributed to satisfaction included Information Quality –

Utilitarian, System Quality – System Efficiency, and Interaction Quality – Cooperation and Care. Conversely, user dissatisfaction largely stemmed from issues in the same dimensions, such as Information Quality – Utilitarian, Interaction Quality - Cooperation, and System Quality – System Reliability. This demonstrated that while the same dimensions could be strengths, their weaknesses could also become threats if not addressed appropriately.

Based on these findings, the research proposed several strategic recommendations for the developers of the Kimia Farma Mobile application, including the development of an FAQ feature, the addition of a validation system and automatic logic to handle OTP requests, Quality Assurance optimization, the establishment of an integrated stock center with dedicated personnel (PIC), optimization of the call center function, chatbot implementation, customer journey simplification, payment integration, automatic refund procedures, and adjustment of the algorithm for automatic voucher return when transactions failed. These improvements were believed to not only be able to increase the application's rating and number of downloads but also directly impact the increment of company's revenue.

However, this research had several limitations that needed to be considered. First, the review data used was comprehensive data without time filtering, so current changes in user perception were not depicted in an updated manner. Second, the analysis only used two sentiment analysis algorithms and the RapidMiner tool without comparison to other algorithms that might offer higher accuracy or efficiency. Third, the data annotation process was performed by only two individuals, which potentially limited the objectivity and validity of the classification results.

Therefore, future research suggests considering the use of review data that is filtered based on a specific time range to observe trends in sentiment changes. Additionally, the exploration of other sentiment analysis methods, as well as the use of alternative tools that can enrich the analysis results, is recommended. Research should also involve more competent annotators to increase the reliability of the data annotation process. Future research can investigate the influence of service quality improvements on application performance.

For the developers of the Kimia Farma Mobile application, the evaluation of user reviews should be carried out periodically to detect recurring problems and identify service areas that require improvement. The application development strategy must focus on improving service quality comprehensively, encompassing the information presented, the quality of interaction with users, and system reliability. This comprehensive and data-driven approach becomes an important step in building a sustainable and responsive digital healthcare service ecosystem that meets user needs.

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