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Aspect-Based Sentiment Analysis of Indonesian Healthcare Application Reviews Using Latent Dirichlet Allocation and IndoBERT

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Abstract
The increasing use of digital healthcare applications has generated large volumes of user reviews that reflect user experiences and satisfaction. This study aimed to perform Aspect-Based Sentiment Analysis (ABSA) of Indonesian healthcare application reviews using Latent Dirichlet Allocation (LDA) and IndoBERT. Unlike previous studies that applied topic modeling or sentiment analysis independently, this study integrated both approaches to identify discussion aspects and their associated sentiment polarities simultaneously. A total of 3,000 reviews were collected from Halodoc, Alodokter, and SATUSEHAT Mobile through the Google Play Store. After preprocessing, 1,460 valid reviews were analyzed. LDA was applied to identify discussion aspects, while IndoBERT was used to classify review sentiments into positive, neutral, and negative categories. The analysis identified seven major aspects related to consultation services, doctor responsiveness, medication delivery, payment processes, and system accessibility. Negative sentiment dominated the dataset (51.78%), followed by positive (40.82%) and neutral (7.40%) sentiments. Doctor Responsiveness and Service Quality achieved the highest positive sentiment (86.57%), whereas Login, OTP, and System Access Problems showed the highest negative sentiment (89.71%). The proposed integration provided more comprehensive insights into aspect-level user perceptions than analyzing topics or sentiments separately. The study concluded that improvements in system reliability, authentication mechanisms, payment services, and medication delivery processes are essential to enhance user satisfaction with Indonesian healthcare applications.

1. Introduction
The rapid advancement of information technology has significantly transformed healthcare service delivery worldwide. Digital healthcare applications have emerged as important platforms that enable users to access medical consultations, health information, appointment scheduling, prescription services, and health monitoring through mobile devices [1]. These applications improve accessibility and convenience by reducing geographical and time barriers, allowing users to obtain healthcare services without visiting hospitals or clinics physically. Consequently, digital health platforms have become increasingly important in supporting modern healthcare systems.

In Indonesia, the adoption of healthcare applications has grown substantially in recent years. Popular platforms such as Halodoc, Alodokter, and SATUSEHAT Mobile provide various digital health services, including online consultations, electronic prescriptions, vaccination records, health screening services, and personal medical information management [2]. The increasing number of users has generated a large volume of online reviews on application marketplaces such as Google Play Store. These reviews contain valuable information regarding user experiences, satisfaction levels, service quality, technical issues, and expectations toward healthcare applications.

User reviews represent an important source of feedback for evaluating digital services. Unlike traditional surveys, online reviews are generated voluntarily and reflect real user experiences [3]. Previous studies have demonstrated that review analysis can provide insights into customer satisfaction, service quality assessment, and product improvement opportunities [4]. However, manually analyzing thousands of reviews is time-consuming and impractical due to the large volume of textual data. Therefore, Natural Language Processing (NLP) techniques have become increasingly popular for extracting meaningful information from user-generated content.

Among NLP approaches, Topic Modeling and Sentiment Analysis are widely used to understand user opinions. Topic Modeling identifies major discussion themes within textual data, while Sentiment Analysis determines the emotional polarity expressed in reviews. Latent Dirichlet Allocation (LDA) is one of the most commonly used topic modeling techniques because of its ability to discover latent topics from large document collections [5]. Meanwhile, transformer-based language models such as IndoBERT have demonstrated superior performance in Indonesian sentiment classification tasks by capturing contextual semantic information more effectively than traditional machine learning approaches [6] Unlike conventional methods that rely on handcrafted features or static word representations, IndoBERT is pre-trained on large-scale Indonesian corpora, enabling it to understand contextual word meanings, linguistic variations, and semantic relationships more accurately. These capabilities make IndoBERT particularly suitable for analyzing informal and diverse user reviews written in the Indonesian language.

Although previous studies have successfully applied topic modeling or sentiment analysis to healthcare application reviews, most studies have analyzed these approaches independently. Topic modeling identifies discussion themes without considering users' emotional responses, whereas sentiment analysis determines overall opinion polarity without identifying the specific service aspects responsible for these sentiments. Consequently, existing studies provide limited insights into which healthcare service aspects contribute to user satisfaction or dissatisfaction. This limitation is particularly evident in studies involving Indonesian healthcare applications, where comprehensive aspect-level sentiment analysis remains relatively unexplored.

Therefore, this study proposes an Aspect-Based Sentiment Analysis (ABSA) framework by integrating Latent Dirichlet Allocation (LDA) and IndoBERT to analyze user reviews of Indonesian healthcare applications. Unlike previous studies that focused solely on topic extraction or sentiment classification, the proposed framework combines automatic aspect discovery with contextual sentiment classification to reveal users' opinions toward specific healthcare service aspects. A dataset consisting of 3,000 Google Play Store reviews from Halodoc, Alodokter, and SATUSEHAT Mobile was analyzed. LDA was employed to identify dominant discussion aspects, while IndoBERT was utilized to classify review sentiments into positive, neutral, and negative categories [7]. The integration of these methods provides a more comprehensive understanding of user perceptions and offers practical recommendations for improving digital healthcare services in Indonesia [8].

2. Research Method

This study employed an Aspect-Based Sentiment Analysis (ABSA) framework to analyze user reviews of Indonesian healthcare applications. The proposed framework consisted of five main stages: data collection, text preprocessing, aspect extraction using Latent Dirichlet Allocation (LDA), sentiment classification using IndoBERT, and model evaluation.

2.1. Data Collection

The dataset used in this study was obtained from user reviews available on Google Play Store. Three widely used healthcare applications in Indonesia were selected as research objects, namely Halodoc, Alodokter, and SATUSEHAT Mobile. Review data were collected using the Python library google-play-scraper. To ensure balanced representation among applications, 1,000 reviews were collected from each application, resulting in a total of 3,000 reviews. Table 1 presents the distribution of collected reviews. Each review record contains several attributes including application name, review date, rating score, review text, number of likes, and application version. These attributes provide contextual information for subsequent analysis. To better describe the dataset, Table 2 summarizes the overall characteristics of the collected data.

Table 1. Distribution of user reviews

Application	Number of Reviews
Halodoc	1,000
Alodokter	1,000
SATUSEHAT Mobile	1,000
Total	3,000

Table 2. Dataset characteristics

Item	Value
Data Source	Google Play Store
Applications Analyzed	Halodoc, Alodokter, SATUSEHAT Mobile
Total Reviews Collected	3,000
Reviews per Application	1,000
Valid Documents after Preprocessing	1,460
Topic Modeling Technique	Latent Dirichlet Allocation (LDA)
Topic Configurations Evaluated	3, 4, 5, 6, and 7 Topics
Selected Topic Model	7 Topics
Highest Coherence Score	0.4823 (3 Topics)

2.2. Text Preprocessing

The preprocessing pipeline consisted of text cleaning to remove URLs, punctuation, numbers, emojis, and special characters, followed by case folding to convert all characters into lowercase. Word normalization was then performed to transform informal Indonesian expressions into standard vocabulary using a manually constructed normalization dictionary. Subsequently, stopword removal was applied to eliminate common Indonesian words carrying limited semantic information, and document filtering was conducted to remove reviews containing fewer than three meaningful words after preprocessing. The resulting cleaned textual dataset was used as the input for both the LDA and IndoBERT models.

2.3. Aspect Extraction Using Latent Dirichlet Allocation

Aspect extraction was performed using Latent Dirichlet Allocation (LDA), an unsupervised probabilistic topic modeling algorithm proposed by Blei et al. LDA assumes that each document consists of multiple latent topics, while each topic is represented by a probability distribution over words. The probability of observing a word in a document can be expressed as:

$$P(w) = \sum_{k=1}^{K} P(w|z_k)\ P(z_k|d) \tag{1}$$

where $P(w)$ denotes the probability of observing word w, $P(w|z_k)$ represents the probability of word w given topic z_k, $P(z_k|d)$ denotes the probability of topic z_k appearing in document d, and K represents the total number of latent topics [9], [10], [11].

The LDA model was implemented using the Gensim library. Several topic configurations ranging from three to seven topics were evaluated. The final number of topics was selected based on coherence score analysis and manual interpretation of topic quality. After topic generation, the keywords within each topic were examined and assigned semantic labels representing user discussion aspects. The parameter configuration used for the LDA model is shown in Table 3.

Table 3. Dataset characteristics

Parameter	Value
Random State	42
Passes	20
Alpha	Auto
Topic Candidates	3-7
Library	Gensim

2.4. Aspect Extraction Using Latent Dirichlet Allocation

After aspect extraction, sentiment classification was performed using IndoBERT, a transformer-based language model pre-trained on large-scale Indonesian corpora. IndoBERT has demonstrated strong performance in various Indonesian Natural Language Processing (NLP) tasks, including sentiment analysis, text classification, and opinion mining. In this study, each preprocessed review was first tokenized using the IndoBERT tokenizer to convert the input text into token IDs compatible with the model. The tokenized reviews were then processed by the pre-trained IndoBERT encoder to generate contextual representations that capture semantic relationships between words within each review. Subsequently, these contextual embeddings were passed to the classification layer, which estimated the probability of each sentiment class through a Softmax function. The predicted sentiment label corresponded to the class with the highest probability among the three predefined categories: Positive, Neutral, and Negative. The sentiment prediction process can be formulated as:

$$\hat{y} = \arg\max P\ (y|x) \tag{2}$$

where x denotes the input review text, y represents the sentiment class, and $\hat{y}$ is the predicted sentiment label with the highest probability [12], [13], [14]. Finally, the sentiment labels generated by IndoBERT were integrated with the dominant topics obtained from LDA to perform Aspect-Based Sentiment Analysis (ABSA), enabling sentiment identification for each healthcare service aspect discussed by users.

2.5. Model Evaluation

The quality of the generated topics was evaluated using the Coherence Score metric. Topic coherence measures the semantic similarity among the most representative words within a topic. Higher coherence values generally indicate more interpretable and semantically consistent topics. The coherence metric can be expressed as:

$$Coherence(T) = \frac{1}{N}\sum_{i=1}^{N} score(w_i, w_j) \quad (3)$$

Where T denotes a topic, N denotes the total number of evaluated word pairs, and $score(w_i, w_j)$ represents the semantic similarity score between words w_i and w_j [15], [16].

Higher coherence values indicate more interpretable and meaningful topics. The topic configuration with the highest coherence score was selected as the final LDA model. Finally, aspect extraction results and sentiment classification outputs were integrated to identify dominant user perceptions regarding Indonesian healthcare applications. The findings were analyzed descriptively through topic distribution, representative reviews, sentiment composition, and aspect-level interpretation.

3. Resulth & Discussion

3.1. Topic Modeling Results

This study analyzed user reviews collected from three major Indonesian healthcare applications, namely Halodoc, Alodokter, and SATUSEHAT Mobile. A total of 3,000 reviews were obtained from the Google Play Store in May 2026, consisting of 1,000 reviews from each application. The balanced dataset was designed to provide comparable representations of user experiences across different digital healthcare platforms.

Figure 1 presents the distribution of reviews for each application. The results show that each application contributed an equal number of reviews, ensuring that no platform disproportionately influenced the subsequent topic modeling and sentiment analysis processes.

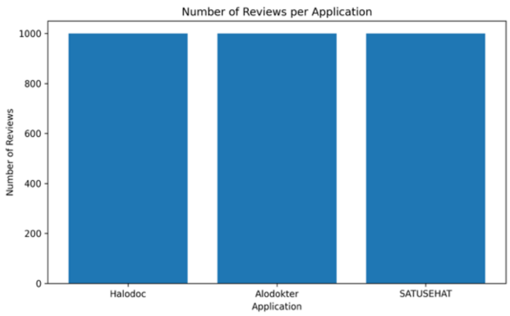

Figure 1. Number of Reviews Collected from Each Healthcare Application

In addition, the average rating differs across applications. Halodoc achieved the highest average rating (4.539), followed by Alodokter (4.203), while SATUSEHAT Mobile obtained a considerably lower average rating (3.014). These differences suggest variations in user satisfaction levels among healthcare applications and motivate further investigation through topic modeling and sentiment analysis.

3.2. Topic Modeling Results

To identify the main discussion themes in user reviews, Latent Dirichlet Allocation (LDA) was applied to the preprocessed corpus. Several topic configurations ranging from three to seven topics were evaluated using coherence scores. Although the three-topic model achieved the highest coherence score (0.4823), the seven-topic model was selected for the final analysis because it generated more specific and interpretable aspects that better represented diverse user experiences in healthcare applications. Therefore, the seven-topic model was considered more suitable for the subsequent Aspect-Based Sentiment Analysis (ABSA) process.

Table 4 presents the identified topics and their corresponding interpretations based on dominant keywords and representative reviews. The extracted topics cover both service-related and technical aspects, including medication delivery, online consultation experiences, system access issues, consultation quality, payment processes, and doctor responsiveness.

Table 4. LDA topic interpretation

Topic	Aspect Interpretation
T1	Drug Delivery and Medication Services
T2	Online Consultation Experience
T3	General User Satisfaction
T4	Login, OTP, and System Access Problems
T5	Doctor Consultation Services
T6	Payment, Refund, and Delivery Issues
T7	Doctor Responsiveness and Service Quality

Figure 2 illustrates the distribution of dominant topics across the review corpus. The results indicate that Doctor Consultation Services (T5) is the most frequently discussed topic, accounting for 296 reviews (20.27%), followed by Doctor Responsiveness and Service Quality (T7) with 268 reviews (18.36%), and Login, OTP, and System Access Problems (T4) with 243 reviews (16.64%). These findings suggest that users primarily focus on interactions with healthcare professionals and the accessibility of digital health services.

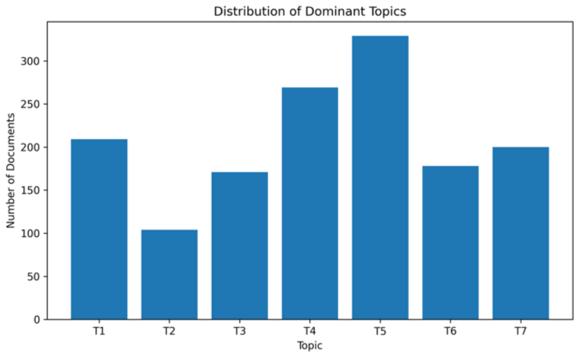

Figure 2. Distribution of dominant topics

The prevalence of consultation-related topics demonstrates that online medical consultation remains a central feature of healthcare applications. However, the substantial proportion of reviews associated with login failures, OTP verification issues, and account access problems indicates that technical barriers continue to affect user experiences. Furthermore, topics related to medication delivery and payment services also appear frequently, suggesting that operational and transactional services constitute important factors influencing user perceptions of healthcare platforms.

Overall, the topic modeling results reveal that user discussions are not limited to medical consultations alone but also encompass technical system performance and supporting service quality. These findings provide a foundation for further sentiment analysis using IndoBERT to examine users' attitudes toward each identified aspect.

3.3. IndoBERT Sentiment Analysis Results

To investigate users' opinions toward healthcare applications, sentiment classification was performed using the IndoBERT model. Unlike topic modeling, which identifies discussion themes, sentiment analysis determines the emotional polarity expressed in each review. The model classified reviews into three categories: positive, neutral, and negative.

Table 5 presents the overall sentiment distribution obtained from 1,460 reviews that remained after the preprocessing stage. The results indicate that negative sentiment is slightly dominant, accounting for 756 reviews (51.78%). Positive sentiment represents 596 reviews (40.82%), while neutral sentiment accounts for only 108 reviews (7.40%).

Table 4. LDA topic interpretation

Sentiment	Number of Reviews	Percentage (%)
Positive	596	40.82
Neutral	108	7.40
Negative	756	51.78
Total	1460	100.00

The predominance of negative sentiment suggests that users frequently express dissatisfaction regarding certain aspects of healthcare applications. Examination of representative reviews reveals that many negative comments are associated with technical issues, including login failures, OTP verification problems, application instability, payment difficulties, and medication delivery delays. These issues directly affect user experiences and often become the primary reason for low ratings.

Nevertheless, a substantial proportion of positive reviews was also identified. Positive feedback mainly highlights responsive doctors, clear medical explanations, convenient online consultations, and the accessibility of healthcare services without requiring physical visits to hospitals or clinics. This finding indicates that users generally appreciate the healthcare services provided through digital platforms, although several operational and technical challenges remain unresolved.

Overall, the sentiment analysis results demonstrate a contrast between the quality of healthcare services and the reliability of supporting system features. Therefore, further analysis at the aspect level is necessary to identify which specific topics contribute to positive and negative user perceptions. This objective is addressed through the Aspect-Based Sentiment Analysis presented in the following section.

3.4. Aspect-Based Sentiment Analysis

Aspect-Based Sentiment Analysis (ABSA) was conducted by integrating the aspects identified through LDA topic modeling with sentiment labels generated by the IndoBERT classifier. This approach enables a more detailed understanding of user opinions by revealing not only the sentiment polarity but also the specific service aspects that trigger positive or negative perceptions. Table 6 summarizes the sentiment distribution across the seven identified aspects. The results reveal substantial variations in user perceptions depending on the aspect being discussed.

Table 5. Sentiment distribution by aspect

Aspect	Positive (n)	Positive (%)	Neutral (n)	Neutral (%)	Negative (n)	Negative (%)	Total
Doctor Consultation Services	217	73.31	26	8.78	53	17.91	296
Doctor Responsiveness and Service Quality	232	86.57	4	1.49	32	11.94	268
Drug Delivery and Medication Services	63	29.86	16	7.58	132	62.56	211
General User Satisfaction	41	30.15	9	6.62	86	63.24	136
Login, OTP, and System Access Problems	6	2.47	19	7.82	218	89.71	243
Online Consultation Experience	17	9.6	11	6.21	149	84.18	177
Payment, Refund, and Delivery Issues	20	15,5	23	17,83	86	66,67	129

The highest proportion of positive sentiment was observed in the Doctor Responsiveness and Service Quality aspect, where 86.57% of reviews were classified as positive. Users frequently praised doctors for providing fast responses, professional communication, detailed explanations, and effective medical recommendations. Similarly, the Doctor Consultation Services aspect also received predominantly positive evaluations, with 73.31% positive reviews. These findings indicate that healthcare professionals represent the strongest component of user satisfaction within Indonesian healthcare applications.

In contrast, the most negative aspect was Login, OTP, and System Access Problems, with 89.71% of reviews expressing negative sentiment. Common complaints included failed login attempts, invalid PIN notifications, delayed OTP delivery, account verification issues, and inability to access application features. The extremely high proportion of negative sentiment highlights persistent usability and authentication challenges that significantly affect user experiences. Another aspect with a strong negative tendency was Online Consultation Experience, where 84.18% of reviews were classified as negative. Users frequently reported consultation sessions ending automatically before issues were resolved, delayed doctor responses during active sessions, and dissatisfaction with limited consultation duration. Although online consultation remains a key feature of healthcare applications, these operational limitations reduce user satisfaction and perceived service effectiveness.

Negative perceptions were also identified in Payment, Refund, and Delivery Issues (66.67% negative) and Drug Delivery and Medication Services (62.56% negative). Reviews within these aspects often mentioned delayed medication delivery, incorrect shipments, refund processing delays, failed transactions, and inadequate customer support. These findings suggest that supporting operational services remain an important source of user dissatisfaction despite the availability of digital healthcare features.

Interestingly, the General User Satisfaction aspect exhibited a predominantly negative sentiment distribution (63.24% negative), indicating that users who provided overall evaluations often emphasized shortcomings rather than strengths. This pattern suggests that users are generally more motivated to submit reviews when experiencing problems, a phenomenon commonly observed in online review platforms.

Overall, the ABSA results demonstrate that user satisfaction is strongly associated with the quality of doctor interactions, while dissatisfaction is primarily driven by technical system issues and supporting operational services. Therefore, improving authentication mechanisms, consultation workflows, payment processes, and medication delivery systems should become strategic priorities for healthcare application providers in Indonesia.

3.5. Discussion

The integration of LDA topic modeling and IndoBERT sentiment analysis provides a comprehensive understanding of user experiences with Indonesian healthcare applications. The topic modeling results reveal that user discussions are concentrated on consultation services, doctor responsiveness, medication delivery, payment processes, and system accessibility. These findings indicate that healthcare applications are evaluated not only based on medical services but also on the reliability of supporting digital infrastructure.

The sentiment analysis results demonstrate a clear contrast between healthcare service quality and technical system performance. Aspects related to doctors, including consultation services and responsiveness, received predominantly positive evaluations. Users frequently appreciated professional communication, detailed medical explanations, and the convenience of obtaining healthcare services remotely. This finding suggests that healthcare professionals contribute significantly to user satisfaction and represent a major strength of digital healthcare platforms.

In contrast, aspects associated with authentication and operational services generated substantial negative sentiment. Login failures, OTP verification issues, account access problems, delayed medication delivery, unsuccessful payment transactions, and refund difficulties were repeatedly reported across user reviews. These issues negatively affect user trust and may reduce the perceived effectiveness of healthcare applications despite the quality of medical consultations provided.

The findings highlight the importance of balancing healthcare service quality with system reliability. While digital healthcare applications have successfully expanded access to medical consultations, technical and operational challenges remain critical barriers to user satisfaction. Therefore, healthcare application providers should prioritize improvements in authentication mechanisms, platform stability, payment systems, customer support, and medication delivery services. Addressing these issues may enhance user experience and strengthen public acceptance of digital healthcare technologies in Indonesia.

Furthermore, this study demonstrates that the combination of LDA and IndoBERT is effective for extracting service aspects and identifying user sentiment from large-scale review datasets. The proposed approach provides actionable insights that can assist developers, healthcare providers, and policymakers in evaluating and improving digital health services based on user-generated feedback.

4. Conclusion

This study proposed an Aspect-Based Sentiment Analysis (ABSA) framework for analyzing user reviews of Indonesian healthcare applications by integrating Latent Dirichlet Allocation (LDA) and IndoBERT. A total of 3,000 reviews were collected from three major healthcare applications, namely Halodoc, Alodokter, and SATUSEHAT Mobile. After preprocessing, 1,460 valid reviews were analyzed. The LDA model identified seven major aspects of user discussions, including Drug Delivery and Medication Services, Online Consultation Experience, General User Satisfaction, Login, OTP, and System Access Problems, Doctor Consultation Services, Payment, Refund, Delivery Issues, and Doctor Responsiveness and Service Quality. Furthermore, IndoBERT successfully classified user reviews into positive, neutral, and negative sentiment categories, enabling aspect-level sentiment analysis.

The results reveal that aspects related to healthcare professionals received the most favorable evaluations. Doctor Responsiveness and Service Quality achieved the highest proportion of positive sentiment (86.57%), followed by Doctor Consultation Services (73.31%). In contrast, Login, OTP, and System Access Problems exhibited the highest proportion of negative sentiment (89.71%), followed by Online Consultation Experience (84.18%). These findings indicate that users generally appreciate the quality of medical consultations and doctor interactions provided by healthcare applications. However, technical issues, authentication failures, payment processes, and medication delivery services remain major sources of dissatisfaction. Therefore, healthcare application providers should prioritize improvements in system reliability, user authentication mechanisms, payment services, and operational support to enhance user experience and increase public trust in digital healthcare platforms. Future studies may incorporate larger datasets, additional healthcare applications, and more advanced transformer-based language models to provide deeper insights into user perceptions of digital health services.

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