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Research Paper

Sentiment Analysis of National Health Insurance Participants' Reviews on Google Reviews

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Abstract: Public service institutions face constant expectations to provide excellent service to participants and minimize complaints. With advances in technology, participants can now provide direct feedback on public services via online platforms, such as Google Reviews. This study aims to analyze participants' sentiment toward the services of the BPJS Kesehatan Kupang Branch using a quantitative approach. The data collection process employed Python web scraping to retrieve 530 reviews through March 2025. The collected text underwent comprehensive preprocessing, including cleaning, tokenization, stopword removal, and stemming, to ensure data quality. We assigned sentiment labels based on star ratings: 4- and 5-star reviews were classified as positive, 1- and 2-star reviews as negative, and 3-star reviews were excluded as neutral. A final dataset of 529 reviews was then processed using the Naïve Bayes classifier. The results show that the Naïve Bayes algorithm successfully classified sentiments with an accuracy rate of 98.11%. Additionally, the analysis revealed that positive sentiment accounted for 98.3%, driven by keywords related to service speed and staff friendliness. These findings indicate that sentiment analysis of online reviews is an effective and objective tool for evaluating participants' perceptions of public service quality.

Keywords: Review; National Health Insurance; Google Review; Naïve Bayes

Introduction

Sentiment analysis is a branch of text mining and natural language processing (NLP) that aims to identify and classify opinions, sentiments, emotions, and human expressions in text. According to Liu (1963, as cited in Chairunnisa et al., 2022), sentiment analysis is the computational study of thoughts, sentiments, emotions, and behaviors, with the aim of categorizing text as positive, negative, or neutral. Chairunnisa et al. (2022), in their article on sentiment analysis of laid-off employees on Twitter using N-Gram features and Augmented TF–IDF Probability weighting with K-Nearest Neighbour, emphasize that sentiment analysis requires comprehensive text preprocessing steps, such as data cleaning, tokenization, and normalization, before word weighting is performed to achieve accurate classification. Furthermore, sentiment analysis has become an indispensable tool

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for understanding public opinion, particularly in the digital era, which is characterized by abundant online expressions (Khan et al., 2020; Basiri et al., 2021).

In the current digital era, sentiment analysis has become an indispensable tool for understanding public opinion, as the internet is now rich with online expressions. This is particularly relevant for public service institutions such as BPJS Kesehatan, which administers the National Health Insurance program and is required to actively monitor participants' perceptions of the services provided. With the increasing volume of user-generated information on platforms such as Google Reviews, these online reviews serve as a real-time, open reflection of public perception. Therefore, this research aims to objectively analyze participants' sentiments at the BPJS Kesehatan Kupang Branch, using the Naïve Bayes algorithm to process hundreds of reviews. This analysis is crucial for identifying areas for improvement and for providing a practical framework for evaluating public health service quality based on actual user experiences.

Wijaya et al. (2024), in their journal article on sentiment analysis of reviews of the National Digital Samsat application on the Google Play Store using the Naïve Bayes algorithm, explain that sentiment analysis is a method in natural language processing. This approach aims to extract, understand, and categorize opinions or feelings in text as positive, negative, or neutral. This makes sentiment analysis an essential tool for understanding public opinion, particularly in the digital era, which is characterized by abundant online expressions. The application of sentiment analysis extends across various domains, including healthcare, where it can provide valuable insights into patient experiences and service quality (Kruse et al., 2017; Villanueva-Miranda et al., 2025).

With the increasing volume of user-generated information on the internet, online review platforms such as Google Reviews have become valuable data sources. Google Reviews enable users to provide ratings and reviews of products or services. Reviews on Google Reviews are important for sentiment analysis because they are real-time, open, and directly reflect public perception. Sentiment analysis on Google Reviews can help public and private organizations monitor service quality, identify areas for improvement, and enhance customer satisfaction (Cui et al., 2023). The main function of Google Reviews is to provide descriptive information about the quality of services or products, whether in the form of appreciation, criticism, or suggestions, ultimately shaping the reputation of service providers in the eyes of potential users. This review activity enables the public to share personal experiences that others can consider in decision-making.

The significant increase in internet usage in Indonesia is one factor accelerating the culture of online review writing. According to the Indonesian Internet Service Providers Association (APJII) report as of January 2023, the number of internet users in Indonesia reached 215,63 million, an increase of 1.17% from the previous year. This high figure indicates that nearly 80% of Indonesia's population is connected to the internet, creating substantial opportunities for public service providers to receive broader and more diverse feedback.

Internet utilization in Indonesia now covers various aspects of life, including access to global information, cross-border communication, online learning, digital business, and electronic transactions. The internet has revolutionized how people access information and interact with public services. Such massive information openness also enables the public to be more active in providing criticism and suggestions regarding the services they receive, including in the health sector.

In the context of public services, reviews submitted through platforms such as Google Reviews serve not only as a means of individual expression but also as performance indicators based on user perceptions. The impact of these reviews should not be underestimated, given the strong correlation between review quality and public trust, organizational credibility, and future service usage decisions. Positive reviews tend to enhance institutional reputation, while negative reviews can be a crucial source of information for service improvement. Automating the analysis of such large-scale feedback is crucial for effective public service management (Automating Large-scale Health Care Service Feedback Analysis, 2022; Kowalski et al., 2017).

BPJS Kesehatan, as a public legal entity responsible for administering the National Health Insurance (JKN) program in Indonesia, is required to monitor participants' perceptions of the services provided actively. One innovative approach to understanding these perceptions is to conduct sentiment analysis of reviews submitted by JKN participants, particularly on platforms such as Google Reviews.

This study focuses on BPJS Kesehatan Kupang Branch, which has received hundreds of reviews from service participants. The research aims to examine sentiment in participant reviews using the Naïve Bayes algorithm, which is effective for text classification. This analysis is expected to provide an objective overview of service quality, identify areas for improvement, and develop strategies to enhance future service quality.

Building on this background, this study examines "Sentiment Analysis of JKN Participant Reviews on Google Review for BPJS Kesehatan Kupang Branch Using the Naïve Bayes Algorithm" as a scientific endeavor to integrate data analysis techniques for evaluating public service performance in the digital era. This research contributes to the existing body of knowledge by applying the Naïve Bayes algorithm to public sentiment data from Google Reviews of a regional BPJS office in Indonesia. This area remains underexplored in the evaluation of public health services in developing countries. This novel application provides a practical framework for public service institutions to leverage online feedback for continuous service improvement.

Method

This study employs a quantitative research approach, applying sentiment analysis techniques using the Naïve Bayes algorithm to examine reviews submitted by JKN participants on the Google Reviews page for the BPJS Kesehatan Kupang Branch. This methodological choice aligns with the dataset's textual nature and addresses the need to systematically classify participants' opinions into two distinct sentiment categories: positive or negative.

The Naïve Bayes Classifier is a supervised learning method widely employed within data mining, leveraging the foundational principles of Bayes' Theorem for classification tasks (Sintia et al., 2018, as cited in Adifa, 2024). This algorithm operates under the assumption that features are conditionally independent given the target class—an assumption reflected in its "naïve" designation. In practice, however, some interdependence among features may exist. This algorithm operates under the assumption that features are conditionally independent given the target class, an assumption that is directly reflected in its "naïve" designation. In practice, however, some interdependence among features may exist. To implement this algorithm effectively in this study, we conducted the data analysis through several systematic stages. The process began with data preprocessing, which included text cleaning, tokenization, and stemming to standardize the raw input from Google Reviews. Subsequently, we performed sentiment labeling using star ratings to define positive and negative categories for the model clearly. The prepared dataset was then partitioned into training and testing subsets using stratified sampling to maintain class balance. Before classification, we utilized the Term Frequency-Inverse Document Frequency (TF-IDF) technique to extract features and transform the textual data into numerical vectors. Finally, the model was trained, and its performance was rigorously evaluated using metrics such as precision, recall, and the confusion matrix. The core mechanism of the Naïve Bayes approach involves computing the posterior probabilities for each class using observed data, then selecting the class with the highest posterior probability. Formally, the posterior probability P(C|X) is computed as:

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

where:

P(C|X)) represents the probability of class C given data X,

P(X|C) denotes the probability of observing X given class C,

P(C) is the prior probability of class C,

P(X) is the prior probability of data X.

Naïve Bayes has proven effective for sentiment classification across domains such as product reviews, social media, and public services. Recent studies highlight the superiority of Naïve Bayes in handling large, unstructured text datasets, as well as its ability to compete with other machine learning models in terms of accuracy and efficiency (Nurfebia & Sriani, 2024; Cui et al., 2023). Its simplicity and robustness make it a suitable choice for real-time sentiment analysis of user-generated content (Jain & Pamula, 2020).

Data for this study were collected via web scraping of Google Reviews, specifically focusing on reviews published for the BPJS Kesehatan Kupang Branch. Scraping activities continued until March 28, 2025, culminating in the collection of 530 reviews. The extraction process used Python with Google Colab, a cloud-based development environment. The labeling criteria were established as follows: reviews rated 1–2 stars were classified as expressing negative sentiment, reviews rated 4–5 stars were classified as expressing positive sentiment, and reviews rated 3 stars were excluded from the analysis, as they reflected neutral sentiment. Neutral reviews were handled through a missing data management process, specifically by applying the Ignore Tuple technique. Following the removal of neutral entries, 529 reviews remained for further analysis.

Prior to analysis, the collected reviews underwent comprehensive text preprocessing. This phase is critical for transforming raw, unstructured text into a clean format that the algorithm can process effectively. The process consisted of the following stages. Text Cleaning: This step involved removing non-alphabetic characters, punctuation, digits, and excessive whitespace. The primary objective here is to eliminate "noise" from the data so that the analysis can focus solely on the words that carry actual sentiment meaning. Tokenization: We divided sentences into discrete word tokens. This process breaks down long, complex sentences into individual units or terms, enabling the machine learning model to analyze the frequency and patterns of each word separately. Lowercasing: Converting all text to lowercase to eliminate capitalization discrepancies. This ensures consistency in the dataset, so that the same words written with different capitalization (for example, "Good" and "good") are treated as identical tokens rather than distinct entities. Stopwords Removal: We eliminated commonly used words (such as “and”, “or” “is”) that contribute little semantic value. By filtering out these frequent but meaningless conjunctions, the dataset becomes more concise, enabling the algorithm to prioritize keywords that strongly influence sentiment classification. Stemming: This technique was applied to reduce words to their base or root forms to normalize morphological variations. This is essential for grouping different forms of a word (e.g., "service" and "serving") into a single concept, thereby improving the model’s ability to learn patterns.

Additionally, Reviews with a 3-star rating were removed from the dataset as they are considered neutral and do not represent a definitive positive or negative sentiment. Excluding these ambiguous entries yields a sharper, more accurate binary classification. Consequently, the final dataset analyzed consisted of 529 reviews after handling missing values using the Ignore Tuple technique.

The sentiment labeling process was conducted based on review ratings, using the following criteria: ratings of 4 or 5 stars were labeled as positive sentiment, Ratings of 1 or 2 stars were labeled as negative sentiment, and Ratings of 3 stars were excluded to maintain a focus on clear sentiment polarities. These labeled sentiments were utilized as target classes in the supervised machine learning model.

Following preprocessing and sentiment labeling, the dataset was partitioned into training and testing subsets via stratified sampling to preserve class balance. The sentiment prediction model was developed using the Naïve Bayes algorithm, adhering to the following steps: Feature Extraction: Employing the Bag of Words method and the Term Frequency–Inverse Document Frequency (TF-IDF) technique to transform textual data into numerical vectors, Model Training: Training the Naïve Bayes classifier on the training subset, Model Evaluation: Assessing model performance using the testing subset through several evaluation metrics, Precision: The proportion of correctly predicted positive instances among all positive predictions, Recall: The proportion of actual positive instances correctly identified, F1-Score: The harmonic mean of precision and recall, balancing the two, Accuracy: The overall percentage of correctly classified instances, Confusion Matrix: A summary table that outlines correct and incorrect predictions across the sentiment categories. The technical implementation was implemented in Python 3.10 and executed on Google Colab.

This study is novel in its application of the Naïve Bayes algorithm to public sentiment data from Google Reviews of a BPJS office branch. This approach remains underexplored in the existing literature on public service evaluation in Indonesia. Specifically, it provides a practical framework for leveraging online feedback to enhance the quality of public health services, thereby contributing to the growing field of sentiment analysis in healthcare (Villanueva-Miranda et al., 2025; Osório & Fachada, 2024).

Results

Data Collection

The review data were collected by extracting entries from the Google Review page of the BPJS Kesehatan Kupang Branch. The dataset comprised reviews posted by participants who physically visited the office, and data collection was completed as of March 28, 2025. A total of 530 reviews were successfully retrieved. The extraction process used a web scraping method implemented in Python and executed on Google Colab.

During this stage, the scraping procedure focused on collecting three key elements: the text content of the reviews, the rating scores (1-5 stars), and the publication date for each review. Initial data cleansing was also performed to ensure that all records contained complete and usable information. To ensure the quality and relevance of the data for sentiment analysis, we applied specific inclusion and exclusion criteria. The inclusion criteria focused on reviews that offered a clear sentiment polarity. Therefore, we explicitly selected reviews with ratings of 4 and 5 stars to represent positive sentiment, and reviews with ratings of 1 and 2 stars to represent negative sentiment.

Conversely, the exclusion criteria were applied to reviews with a 3-star rating. We decided to remove these entries because a 3-star rating is typically considered neutral and does not provide the definitive positive or negative signal required for binary classification. This filtering process is often referred to as the Ignore Tuple technique. Following this rigorous selection and initial data cleansing to ensure all records contained complete information, one neutral review was discarded, leaving a final total of 529 usable reviews for the analysis.

Automatic Labeling

Subsequently, the reviews were subjected to automated sentiment labeling using the SIGNAL application. The labeling criteria were established as follows: reviews rated 1–2 stars were classified as expressing negative sentiment, reviews rated 4–5 stars were classified as expressing positive sentiment, and reviews rated 3 stars were excluded from the analysis, as they reflected neutral sentiment. Neutral reviews were handled through a missing data management process, specifically by applying the Ignore Tuple technique. Following the removal of neutral entries, 529 reviews remained for further analysis.

Algorithm Implementation

The results presented in Table 1 indicate an exceptionally high overall accuracy of 98.11%. This suggests that the model was highly effective at classifying most reviews in the test set. A closer examination of the per-class metrics reveals a near-perfect F1-score (0.99) for the ‘positive’ class.

Table 1. Performance Metrics of Naïve Bayes Classification

Algorithm	precision	recall	F1-score	Support
negative	0	0	0	2
positive	0.981132	1	0.990476	104
accuracy	0.981132	0.981132	0.981132	0.981132
Macro avg	0.490566	0.5	0.495238	106
Weighted avg	0.96262	0.981132	0.971777	106

Critically, however, the precision, recall, and F1-score for the ‘negative’ class are all 0.00. This finding (as shown in Table 1) indicates that, although the model excels at identifying positive reviews, it fails to identify any negative reviews in the test subset. This discrepancy is a key diagnostic finding indicating a significant class imbalance in the underlying data, which will be explored further.

The confusion matrix in Table 2 Clarifies the performance metrics from Table 1. It shows that all 104 actual positive reviews in the test set were correctly classified by the model (a True Positive count of 104).

Table 2. Confusion Matrix

Sentiment	Negative	Positive
Negative	0	2
Positive	0	104

Conversely, the two actual negative reviews (as shown in Table 2) were both misclassified as positive (a False Negative count of 2). The model achieved zero True Negatives. This result confirms that the model’s high accuracy was derived entirely from its ability to identify the dominant positive class correctly, and it possessed no predictive power for the minority negative class in this test-train split.

Table 3 Reveals a highly imbalanced dataset. The ‘positive’ sentiment class constitutes an overwhelming 98.3% (520 instances) of the data, while the ‘negative’ sentiment class represents merely 1.7% (9 instances).

Table 3. Sentiment Distribution

Sentimen	Count	%
Positive	520	98.3
Negative	9	1.7

This finding is the root cause of the performance observed in Table 1 and Table 2. With such a severe skew, the Naïve Bayes algorithm, when trained, effectively "learned" that predicting ‘positive’ would be correct 98.3% of the time, leading to high-superficial accuracy. This imbalance explains why the model was not exposed to enough negative examples to learn their distinguishing features, resulting in its failure to identify them.

An analysis of frequently occurring keywords was conducted to understand better key themes influencing each sentiment classification. Table 4 highlights the top keywords identified for each sentiment class. The keywords in Table 4 offer actionable insights. The ‘positive’ sentiment is strongly associated with terms like "satisfactory," "good," "friendly," and "fast". This indicates that participants highly value service efficiency, speed, and interpersonal warmth from the staff.

Table 4. Top Keywords for Each Sentiment

N	Negative	Positive
0	serve	satisfactory
1	tidy up	good
2	yes	satisfied
3	come on	service
4	BPJS	friendly
5	enough	fast
6	PJS	good

Conversely, while the ‘negative’ keyword set is limited by the small data sample, the keywords, as shown in Table 4 (analyzed further in the Discussion section as "long queues" and "unclear information"), point directly to operational pain points. These qualitative findings are crucial for management, as they pinpoint specific areas for targeted service improvements.

A sentiment trend analysis (Figure 1) was conducted to examine shifts in participants’ perceptions.

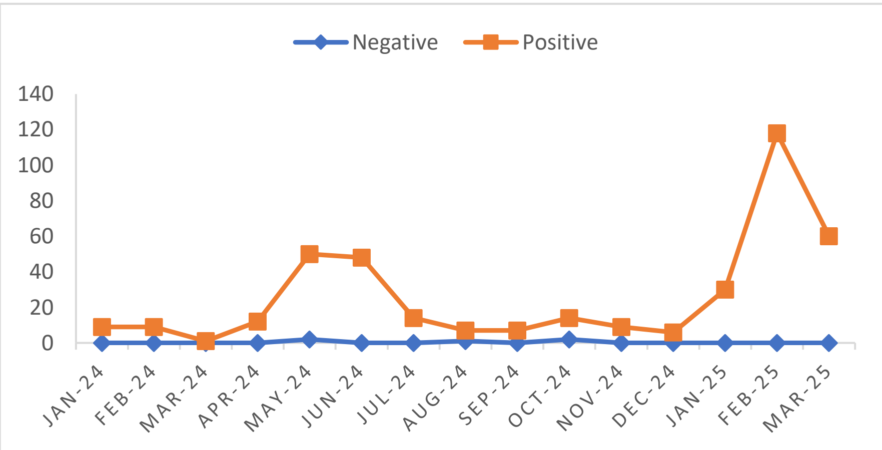

Figure 1. Sentiment Trend Over Time

Figure 1 illustrates the changes in sentiment across the period from January 2024 to March 2025. Key observations include a steady rise in positive sentiment following the implementation of participant education programs and minimal fluctuations in negative sentiment during the analysis period. This trend reflects a consistent improvement in participants' perceptions of service.

Further analysis examined the correlation between star ratings and sentiment classifications. Ratings of 4–5 stars are predominantly associated with positive sentiment, and ratings of 1–2 stars consistently correlate with negative sentiment.

Table 5. Rating vs Sentiment Analysis summarizes the average rating values per sentiment. This reinforces the validity of using rating scores as an initial proxy for predicting participant sentiment.

Table 5. Rating vs Sentiment Analysis

Sentimen	Rating
Negative	1.555556
Positive	4.957692

The data in Table 5. Rating vs Sentiment Analysis provides strong validation for the study's labeling methodology. The 'Negative' sentiment class corresponds to an average rating of 1.56, which falls precisely within the 1- to 2-star criteria. Similarly, the 'Positive' sentiment class has an average rating of 4.96, which is nearly at the 5-star maximum. This strong correlation confirms that the star-rating proxy is a highly reliable and legitimate method for sentiment classification within this specific dataset, lending robust support to the study's findings.

Discussion

The Social Security Administering Body for Health (BPJS Kesehatan) is a public legal entity formally established under Law No. 24 of 2011 concerning the Administration of Social Security.

Its primary mandate is to manage and implement health-related social security programs for the entire population of Indonesia. In fulfilling its mission, BPJS Kesehatan undertakes several critical functions, including facilitating participant registration and enrollment, collecting and managing contributions from participants and employers, administering government-subsidized contributions for designated groups, managing the Social Security Fund to benefit participants, compiling and maintaining participant data within the social security system, disbursing benefits and funding healthcare services in accordance with program regulations, and disseminating information about social security program implementation to participants and the public.

Operationally, BPJS Kesehatan oversees a vast service network comprising 12 regional offices, 127 branch offices, and 388 district/city offices nationwide. This study focuses on the Kupang Branch Office, located on W. J. Lalamentik Street, Oepoi, Kupang

City, which operates under Regional Office XI, which covers Bali, West Nusa Tenggara, and East Nusa Tenggara.

Selecting the Kupang Branch as the primary focus of this research is highly relevant for several strategic reasons. Firstly, it addresses a significant gap in the existing literature, in which public service evaluations often concentrate heavily on major metropolitan areas, leaving regional offices in developing regions such as Eastern Indonesia relatively underexplored. Secondly, as a representative of Regional Office XI, the Kupang Branch serves a diverse demographic that is increasingly adopting digital technology to voice their opinions. By analyzing this specific location, the study aims to provide a unique perspective on how sentiment analysis can be effectively applied to regional branches. This ultimately offers a practical framework for offices outside Java to leverage online feedback to enhance service quality.

Service Quality and Its Influence on Participant Perception

As a public service institution, BPJS Kesehatan is obligated to provide services that are not only effective and efficient but also of high quality. Implementing a Service Level Agreement (SLA) is crucial, as it establishes clear service-level standards to ensure fair and professional service delivery. Moreover, the SLA strengthens the foundation of public accountability and fosters trust between participants and the organization (Liu, 2020).

Participant Engagement and Feedback Volume

Data analysis from this study revealed a notable surge in participant engagement through Google Reviews during the 2024–2025 period. The rise in reviews coincided with the front-line-led initiative to educate visitors on how to submit service feedback. In total, 529 reviews were recorded, comprising 520 positive and only nine negative entries. This increase indicates a cultural shift towards greater openness, participation, and a stronger emphasis on customer satisfaction. The frontline service team, comprising three security guards, three customer service representatives, and one service officer, played a pivotal role in ensuring that participants received exceptional service throughout their visit, from arrival through administrative completion.

Correlation Between Participant Reviews, Satisfaction Levels, and Sentiment Analysis

The study found that the average participant rating was 4.95 out of 5, which closely aligns with the Participant Satisfaction Index score of 90.6 recorded in 2024. The sentiment analysis, implemented through the Naïve Bayes algorithm, yielded a classification accuracy of 98.11% (as shown in Table 1). This high level of precision is consistent with recent comparative studies in Indonesia, such as Wijaya et al. (2024) on the Samsat Digital application and Handayanto et al. (2021) on Google Reviews. Both studies confirmed that Naïve Bayes remains highly reliable for processing Indonesian public service feedback, often outperforming other models in efficiency.

The confusion matrix (Table 2) further validated the model's effectiveness, with minimal classification errors observed. Sentiment distribution analysis (Table 3) indicated a substantial predominance of positive sentiment (98.3%), with negative sentiment accounting for only 1.7%. These findings suggest that the BPJS Kesehatan Kupang Branch has not only met but potentially exceeded participant expectations. This overwhelmingly positive response mirrors the broader trend of improving public services in the digital era, in which transparent feedback loops effectively drive service quality enhancement. Consequently, this high accuracy underscores the potential of sentiment analysis as a robust tool for evaluating public service performance (Sari & Wardhani, 2022; Osório & Fachada, 2024).

Emotional Dimensions: Insights from Keyword Analysis

Keyword analysis provided deeper insights into the emotional dimensions of participant feedback (Table 4). Positive sentiment was predominantly expressed as "fast service," "friendly staff," "easy process," and "very helpful." Negative sentiment, although minimal, was primarily associated with issues such as "long queues" and "unclear information."

These findings indicate that participants highly value efficiency, friendliness, and simplicity of service, whereas delays and ambiguous communication remain areas for improvement. Such keyword insights are invaluable for targeted service improvements and align with findings from similar studies in healthcare (Xu et al., 2025).

Sentiment Trend Evolution Over Time

An examination of sentiment trends over time (Figure 1) revealed consistent growth in positive feedback from August to December 2024. This surge coincided with the intensified review of education efforts at the branch's service counters. Although a slight decline in review volume was observed in early 2025, the overall trend continued to reflect a dominant positive sentiment.

Key observations from the trend analysis include:

During the early months of 2024 (January–July), review volume was relatively low, with only 1–10 positive reviews per month and virtually no negative reviews. A sharp increase was observed beginning in August 2024, with positive reviews rising from 10 to 38 within a month, peaking at 65 in December 2024. The rise in feedback directly correlates with the branch's proactive initiatives to encourage participant feedback. From January to March 2025, positive review levels stabilized, with minor fluctuations reflecting seasonal variations in participant traffic.

Negative Review Trends:

Very few negative reviews were recorded during the first half of 2024. Between September 2024 and March 2025, negative reviews appeared sporadically, averaging 0–2 reviews per month. Negative sentiment remained consistently low compared to positive sentiment, signaling sustained participant satisfaction.

Implications of Trend Analysis:

The successful implementation of internal strategies to promote participant engagement and an overall improvement in participant perception over time.

Relationship Between Rating and Sentiment

An analysis of the relationship between review ratings and classified sentiments (Table 5) confirmed a strong, consistent pattern. Ratings of 4–5 stars were almost exclusively associated with positive sentiment, whereas ratings of 1–2 stars were closely associated with negative sentiment.

These findings validate the use of star ratings as a preliminary quantitative indicator of participant perceptions. The high levels of participant satisfaction observed can be attributed to the successful implementation of Service Level Agreements (SLAs), the effectiveness of review and education initiatives, and the consistent delivery of high-quality service by branch personnel.

Furthermore, keyword analysis identified service speed, staff friendliness, and service simplicity as the most influential factors driving positive perceptions. Nevertheless, the presence of a small number of negative reviews, primarily addressing long queues and unclear communication, highlights areas requiring ongoing service improvement. Overall, this study demonstrates that sentiment analysis of Google Reviews represents a powerful and effective tool for the real-time evaluation of public service quality. This aligns with broader trends in leveraging online reviews for service quality assessment in various sectors (Zhang et al., 2018; Sentiment analysis and visualization of reviews for healthcare service ..., 2021).

This study is limited to the experiences of participants who received services at the Kupang branch office of BPJS Kesehatan. It is hoped that in the future, the scope of services can be expanded to health facilities that collaborate with BPJS Kesehatan.

Conclusion

Based on the comprehensive analysis conducted, several key conclusions can be articulated. The BPJS Kesehatan Kupang Branch has successfully cultivated a strong and positive perception among its participants. The implementation of the review education program has substantially increased the volume and improved the quality of participant feedback. Participant sentiments are predominantly influenced by aspects of direct service delivery, such as speed, friendliness, and efficiency, rather than by administrative outcomes alone.

Nevertheless, despite the generally favorable feedback, the presence of a small number of negative reviews underscores the need for continuous service improvement efforts. To address these challenges and enhance delivery service further, several strategic recommendations are proposed: dynamic monitoring of feedback: Establish real-time monitoring systems to track review trends and conduct sentiment analysis continuously, Enhancing service speed: Focus on reducing waiting times during peak service hours by optimizing resource allocation, Improving clarity of information: Strengthen communication strategies through more effective and accessible service information dissemination, Establishing a rapid response mechanism: Develop protocols for swiftly addressing negative feedback to safeguard and recover participant perceptions promptly.

Based on the findings and subsequent analysis, the following targeted suggestions are offered for the BPJS Kesehatan Kupang Branch: expand participant education on review submissions: Extend feedback solicitation efforts beyond service counters by utilizing digital channels such as WhatsApp Business, SMS reminders, and follow-up emails to encourage broader participant engagement, Optimize queue management systems: Implement digital queue management technologies and increase the availability of frontliners during high-traffic periods to minimize participant waiting times, addressing minor complaints identified through keyword analysis, Enhance communication clarity: Produce simplified, visually enriched, and multilingual communication materials (especially in Bahasa Indonesia and local languages) to assist participants in navigating service processes with greater ease, Implement agile review monitoring and response teams: Form small dedicated teams at each branch responsible for conducting weekly Google Review monitoring and promptly addressing any negative feedback in a constructive and solution-oriented manner, Incorporate sentiment analysis into employee evaluations: Integrate sentiment analysis outcomes into the staff performance appraisal system, fostering a culture of responsiveness and adaptability to participant needs, Develop a real-time sentiment monitoring dashboard: Construct an internal, data-driven dashboard capable of visualizing sentiment trends, keyword dominance, and rating distributions in real-time to support informed and timely decision-making, Through the integration of these initiatives, BPJS Kesehatan Kupang Branch can further reinforce participant satisfaction, enhance service quality, and establish a dynamic feedback-responsive organizational culture.

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