Public Sentiment and Issue Extraction of BPJS Healthcare Services on Social Media Using IndoBERT and LDA

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ABSTRACT

The Social Security Provider Agency (BPJS), available to all citizens of the country, delivers culture - sensitive health care. It's no secret that BPJS, which provides social insurance coverage for the public, always gets a mixture of scolding and satisfaction for its services. Many reviews of BPJS have been posted on social media including YouTube, Instagram and Twitter (X). For this reason, it was necessary to examine developing issues viewed from the public's point of view against BMP services, and provide consideration to the government about which unit needs to be improved and maintained at a satisfactory in quality service. This study dates the KDD(Knowing Discovery in Databases) workflow. Sentiment classification is performed in Indonesian language with IndoBERT model by classifying the sentiments into 3 categories: positive sentiment, neutral sentiment and negative sentiment. Then issue extraction is conducted within each of the sentiment groups via LDA. The statistics in Table 3 also suggest that social media users are positive, neutral and negative by 15.5%, 40.6% and 43.9% respectively, whose extractions imply double issues with respect to each sentiment polarity category. Positive sentiment snippets are issues on public health and welfare, service user BPJS experience and health service quality. Neutral attitude has to do with administration and daily application of BPJS service, including technical procedure like registration, the use of the service itself (healthcare facilities), user interaction facility for BPJS system. Language behaviorCurrently, negative sentiment stems from medical service delivery and prices of BPJS class categories, as well as government policies on premiums.

Keywords-Sentiment Analysis; BPJS; Social Media; Issue Extractions; Indobert; Latent Dirichlet Allocation (LDA); Knowledge Discovery In Database (KDD)

I. INTRODUCTION

The Social Security Administration Agency (BPJS) is responsible for implementing the national health insurance program. According to Law Number 40 of 2004, which outlines the National Social Security System, health insurance is organized nationally based on the principles of social insurance and equity to ensure that participants receive healthcare benefits and protection to meet their basic health needs [1]. Advancements in technology have changed the way people communicate. Thanks to the ubiquitous information access granted by digital media, individuals remain as connected as possible without constraints of place or time [2]. According to DataReportal, as of January 2024, there were 139 million social media users in Indonesia, accounting for 49.9% of the total population [3].

Social media such as YouTube, Instagram and Twitter/X are currently used by the public to voice their objection about BPJS. With the popularity of social media, research on sentiment analysis over the text from these platform has dramatically increased [4]. Opinion Mining enables detection and classification, usually achieving good performances of text recognition[5]. Other techniques that have been applied to sentiment analysis are K- Nearest Neighbors, Decision Tree, and Naive Bayes [6], Support Vector Machine [7], Lexicon-Based and Naive Bayes [8] and Latent Dirichlet Allocation Modeling [9]. This paper builds on a previous study [9] where sentiment was analyzed and issues addressed from negative sentiment towards the BPJS service on Twitter. However, there is a striking contrast of our work which draws from three social media data sources and combines sentiment analysis with topic atoms by LDA (Latent Dirichlet Allocation), a generative statistical model for analyzing textual documents [10].

The objective of this study is to investigate public opinion about BPJS services in Indonesia by sentiment analysis on social media platform (Youtube, Instagram and Twitter) and find out the main issues that appear in positive, negative, and neutral side. This research is useful for BPJS as a reference to improve the quality of service. This research only considers comments about BPJS services in various social media such as YouTube, Instagram, and Twitter (X) from 2022-2024.

II. METHOD

The method of this research is based on the KDD (Knowledge Discovery in Database) framework, as shown in Figure 1. The process started with data selection by taking comments and posts about BPJS which are divided from social media and cleaning data such as remove duplicated data or pre-processing text. The pre-processed data is then classified into positive, neutral and negative sentiments by using IndoBERT and the classification output is normalized. Eventually, sentiment analysis and LDA are performed to retrieve salient topics of each sentiment category while the model's performance is also evaluated to recognize major discussed issues by public.

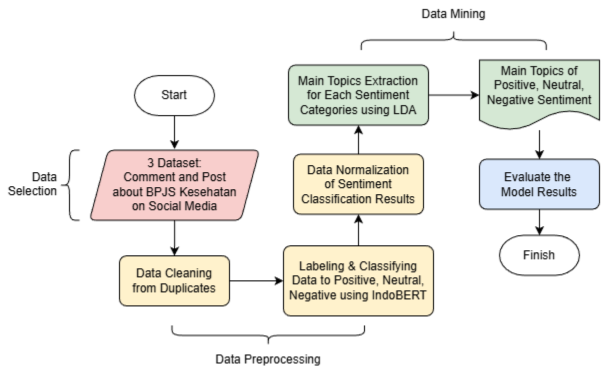


Figure. 1. Research Framework (KDD)

A. Data Selection

Data selection involves choosing relevant data from various sources within a large database for analysis. In this study, the selected data consist of reviews related to BPJS services gathered from the social media platforms YouTube, Instagram, and Twitter (X). The total amount of raw data collected includes 24,167 entries from Instagram, 12,258 from YouTube, and 10,172 from Twitter, resulting in a total of 46,597 raw data points. After the data cleaning process, 21,574 data points from Instagram, 12,050 from YouTube, and 2,595 from Twitter were retained, resulting in a total of 36,219 clean data points.

B. Data Preprocessing

Data pre-processing is the stage used to remove duplicate data and perform labeling using IndoBERT [11]. Figure 2 presents the flowchart of the pre-processing stages. The pre-training stage involves training the IndoBERT model using a large Indonesian text corpus through Next Sentence Prediction (NSP) and the Masked Language Model (MLM). The next step is tokenization, which prepares the text data to allow a machine learning model to read it. In the WordPiece strategy applied in BERT, a text is tokenized into pieces called "token pieces" or "sub-words" [12]. Some additional tokens, e.g., [CLS] (Classification) and [SEP] (Separator), are also appended. The second stage in our constructed pipeline is BERT encoding, which involves plugin the text and yielding numerical vectors that capture the relationships and context of words [13].

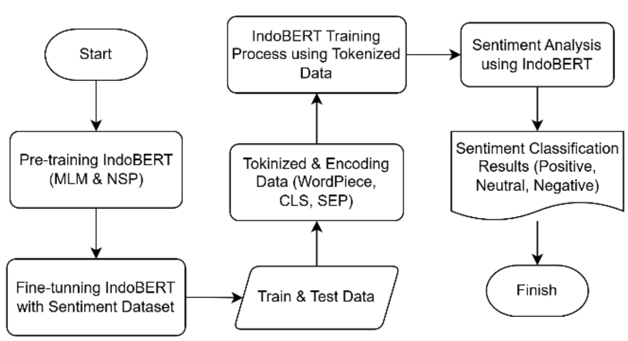


Figure. 2. Labeling Stage using IndoBERT

The results of the pre-processing stage are illustrated in Table 1.

TABLE 1. DATA PREPROCESSING RESULTS

Processing	Results
Full_text	Knp yang udah berjalan ber tahun2 di utak-atik bikin masyarakat menjerit.
Case Folding	knp yang udah berjalan ber tahun utak atik bikin masyarakat menjerit
Tokenisation	['knp', 'yang', 'udah', 'berjalan', 'ber', 'tahun', 'utak', 'atik', 'bikin', 'masyarakat', 'menjerit']
Normalisation	['kenapa', 'yang', 'sudah', 'berjalan', 'ber', 'tahun', 'utak', 'atik', 'bikin', 'masyarakat', 'menjerit']
Stopword Removal	['berjalan', 'utak', 'atik', 'masyarakat', 'menjerit']
Cleaning	berjalan utak atik masyarakat menjerit

The sentiment analysis is done for classification of sentences based on the type of sentiment by using IndoBERT model. From the token [CLS], we can evaluate whether this sentence is positive, neutral or negative. On top of the IndoBERT model, an additional classification layer is stacked. One of the IndoBERT system output example can be seen in Table 2.

TABLE 2. INDOBERT LABELING RESULTS

Comments	Label	Accuration
rek pindah faskes bpjs surabaya ada info puskesmas pelayanannya enak kacamata gigi suwun rek	positive	0,941
pakai bpjs daftar mobile jkn cari google jawabannya	neutral	0,997
bayar iuran bpjs mahal sekalinya sakit dirawat nolak kamar penuh pingsan sialan	negative	0,998

C. Data Transformation

Data transformation Data in its raw form are transformed into other form suitable for analysis and modeling. Normalization is a popular technique in this process that scales numeric features into smaller and similar range. Figure 3 shows the transformation that take place using normalization. The word frequency values from tokenization and vector representations created by IndoBERT are usually identified as the features requiring normalization. In practice, Min-Max Scaling is a widely used technique where feature values are scaled to the range of [0,1].

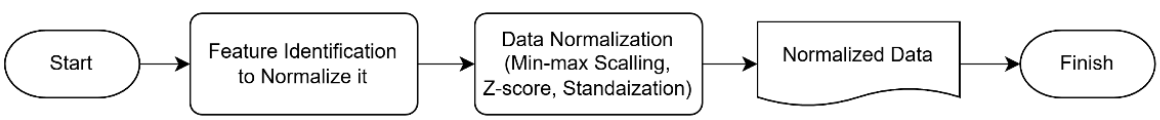


Figure. 3. Data Normalization Flow

One example of normalization are the results shown in Table 3. The subsequent phases are Data Mining and Evaluation, which is covered in the proposed method section.

TABLE 3. NORMALIZATION RESULTS

Words	Freq	Normalization
bpjs	1947	1
kelas	1318	0.676773
......	....	....
kualitas	2	0.000514

III. PROPOSED METHOD

Once the first three stages of KDD process are clear, as a prelude to data modeling, next stage follows covers Data Mining using LDA (Latent Dirichlet Allocation) for sentiment analysis. Finally, the results and findings of this study will be tested Evaluation through a validation testing.

A. Data Mining

When the data is cropped, there are different tools or methods to perform a mining operation [14]. In sentiment analysis, LDA is used to mine issues of positive/negative/neutral sentiments. The LDA method is applied to positive, negative, and neutral sentiment groups to find out the predominant topics discussed more across users within each of the sentiment categories.

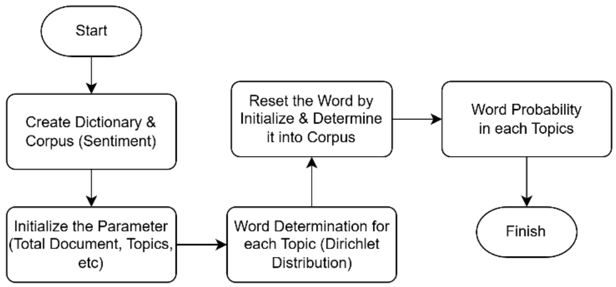


Figure. 4. Topic Extractions Flow using LDA

In general, the underlying process of LDA method in this work is shown in Figure 4. Stemming greedily initialize the parameters such as number of documents, topics and iterations etc; find out word distribution for each topic based on Dirichlet distribution; Genre Topic-Word Probabilities how much different words are likely to be in a topic. Iterations − Iterative calculation of initial parameters and word distributions over entire corpus. In this step, we experimented with the number of topics by testing different increments in the iterations and/or number of K.

B. Evaluation

The evaluation process is an effort to determine if the patterns or information found actually hold true of extant facts or accepted theories [14]. The assessment is then performed by performing a model validation test on the indication of muon spectrum and scattering angle to the incident photon beam, which will be discussed in results and discussion section.

IV. RESULT AND DISCUSSION

In this section, we can see the result and analysis of sentiment analysis of BPJS Issue in public sentiment on social media.

A. Sentiment Result and Analysis

The sentiment value of each document is obtained from calculating the number of positive, negative, and neutral words contained in the document. The sentiment value graph can be seen in Figure 5.

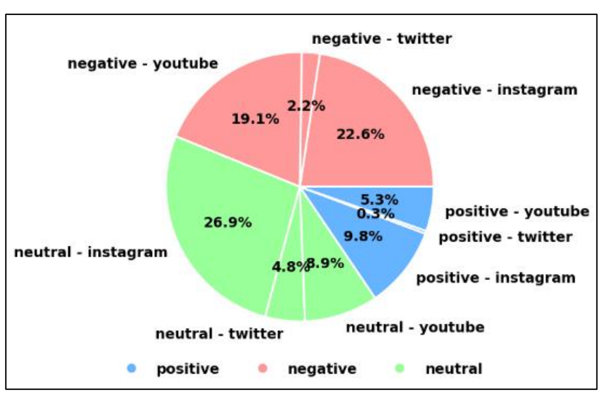


Figure. 5. Sentiment Percentage Graph

On the sentiment analysis of BPJS service, a total 5,487 data were (15.5%) were classified as positive sentiment, 14,397 data (40.6%) was neutral and 15,546 data points (43.9%) was negative from all analyzed 35,431. These results show also that almost half (43.9 %) of all data observed contain unfavorable views toward BPJS services. This indicates that there are many complaints and public displeasure about the program.

B. Extraction Result and Analysis

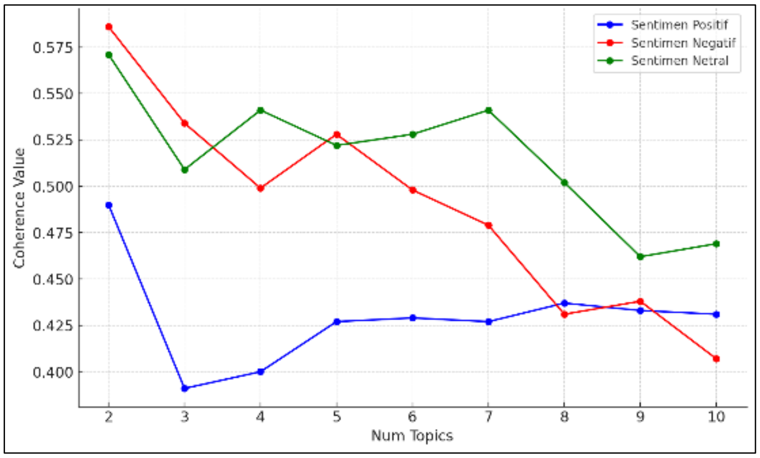


Figure. 6. Topic Coherence Score Graph

The plot of the coherence value calculation per topic in positive, neutral and negative sentiments is shown on Figure 6 where the higher values of coherence for all type sentiment are found in Num Topics = 2 (at 0.49 to positive sentiment, at 0.586 to negative sentiment and by agnostic which was equal with 0.571). This shows that the model with 2 topics gives optimum coherence values which means topics are more consistent and interpretable. Thus, for each sentiment category two topics are extracted as the best if there were. There were two best topics in positive sentiment. Words in each topic are shown in Figure 7 and 8, the larger font size of a word, the higher its possibility to occur. The topic modeling results indicate that Issue 1 is about public's hope, curse, and thanksgiving on the BPJS program. For example, as can be seen in Figure 7, words with highest weights are 'sehat','semoga', and 'bpjs'.. Issue 2 reports on the public´s positive experiences when using BPJS services – such as quality and accessibility, as well as satisfaction with the infrastructure. The words used in this matter are "bpjs," "kelas" (class), and "pelayanan" (service) can be seen in Figure 8.

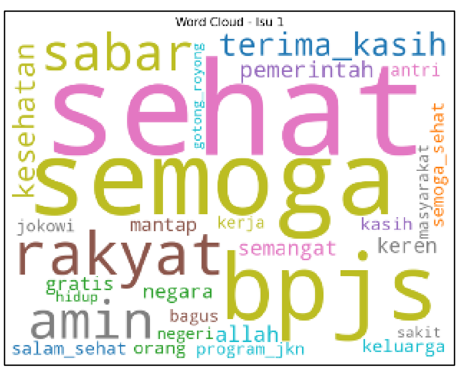


Figure. 7. Issue 1 (positive) Word Cloud

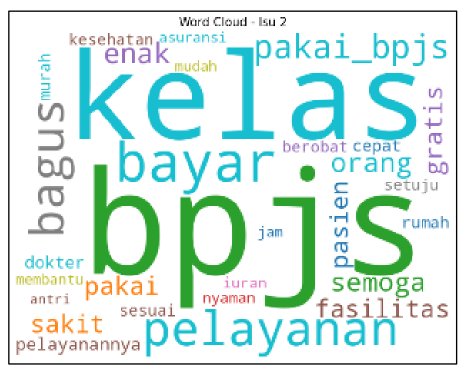


Figure. 8. Issue 2 (positive) Word Cloud

For the Neutral Sentiment, there are also two topics that have maximum likelihood words as shown in Figure 9 and 10. The word cloud of Issue 1 shows words concerning BPJS as reflect "pindah"/move, "ganti"/change, "kantor" (office), anak (child) and suami/husband. These terms are also talk about administration and services of BPJS, such as registration procedures, data changes and service location. The word cloud in Issue 2 also indicates themes associated with BPJS, binding words such "bayar" (pay), "pakai" (use), "kelas" (class), and "iuran" (premium). This shows that focus on the payment and usage of BPJS services simple, namely contributions fees, cclass of service, and inpatient treatment. Words such as "pasien", "rumah sakit" and "puskesmas" highlight the aspect of healthcare services and facilities.

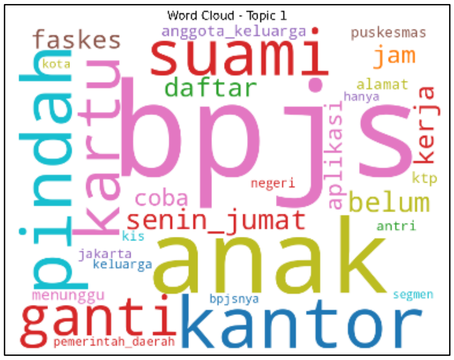


Figure. 9. Issue 1 (neutral) Word Cloud

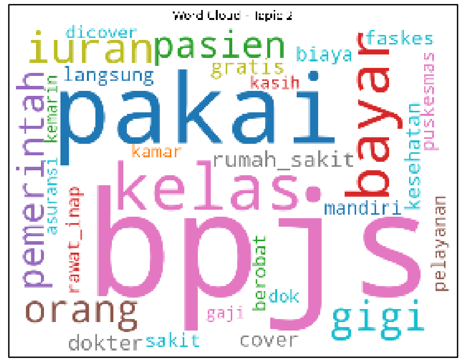
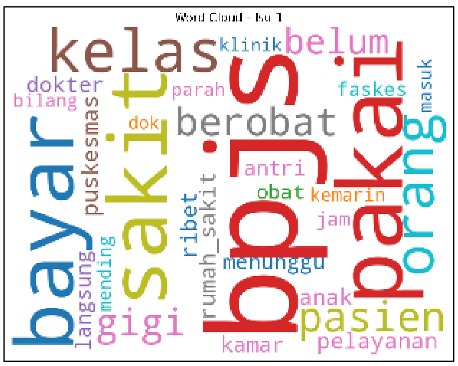


Figure. 10. Issue 2 (neutral) Word Cloud

The negative emotion category also has two best topics, each visualized by the correspondent words appeared in Figure 11 and 12. The observed word relative frequency can be found in Table 4.



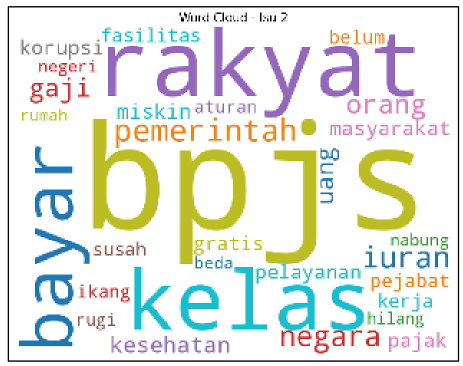


Figure. 11. Issue 1 (negative) Word Cloud

Figure. 12. Issue 2 (negative) Word Cloud

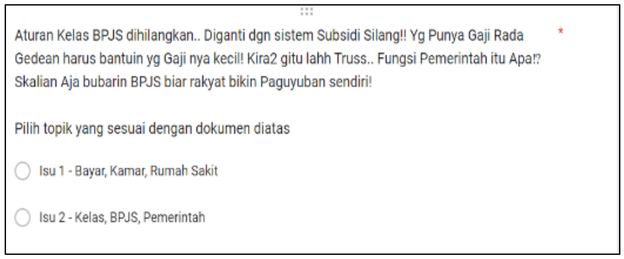
Meanwhile in Issue 2, they are focusing on government policy issues related with the BPJS service, dominant keywords include "pemerintah" (government), "bpjs," ‘kelas” (class), “rakyat” (people), "iuran" (premium) and “fasilitas”. refer to Figure 12. It shows the conversation about government regulation, service level gap, and top-up payment in BPJS system. One such example is a comment from a reader, who talks about his concern regarding the government’s policy for standardised premium rates. Equality in premium is not always the same as equality in treatment, and can be unfair to lower income groups, particularly the poor families of Class 3 who cannot afford either up front fees or hospitalization. The comment suggests also that the policy is deemed expensive and undermining social solidarity.

TABLE 4. PROBABILITY OF NEGATIVE ISSUEEXTRACTION RESULTS

Negative Sentiment			
1st Issue	***Probability***	***2nd Issue***	***Probability***
bpjs	0,070	bpjs	0,034
Pakai	0,031	Rakyat	0,034
Sakit	0,024	Kelas	0,027
Bayar	0.024	Bayar	0,020
Kelas	0,019	Pemerintah	0,015
orang	0,016	Iuran	0,014
pasien	0,013	Negara	0,013
berobat	0,011	Orang	0,012
Gigi	0,011	Gaji	0,011
belum	0,009	Uang	0,009
pelayanan	0,008	Kesehatan	0,008
ribet	0,008	Miskin	0,007
puskesmas	0,008	Masyarakat	0,007
rumah_sakit	0,008	korupsi	0,007

C. Validation Test

Model evaluation was conducted by performing a validation test on the negative sentiment category using a topic instruction task questionnaire. A total of 20 questions were distributed, and 33 respondents participated. The model's accuracy level was measured based on the number of questions correctly answered by the respondents. An example of the questions can be seen in Figure 13.


Aturan Kelas BPJS dihilangkan.. Diganti dgn sistem Subsidi Silang!! Yg Punya Gaji Rada Gedean harus bantuin yg Gaji nya kecil! Kira2 gitu lahh Truss.. Fungsi Pemerintah itu Apa!? Skalian Aja bubarin BPJS biar rakyat bikin Paguyuban sendiri! *

Pilih topik yang sesuai dengan dokumen diatas

- Isu 1 - Bayar, Kamar, Rumah Sakit
- Isu 2 - Kelas, BPJS, Pemerintah

Figure. 13. Question Example

Figure 14 presents a summary of the total scores obtained by all respondents. The average number of correct answers is 0.95, resulting in an interpretation accuracy rate of 95%. These accuracy results indicate that the application of sentiment-based LDA to identify negative issues can be considered optimal, and that respondents found it easy to understand the relationship between an issue and the corresponding document.

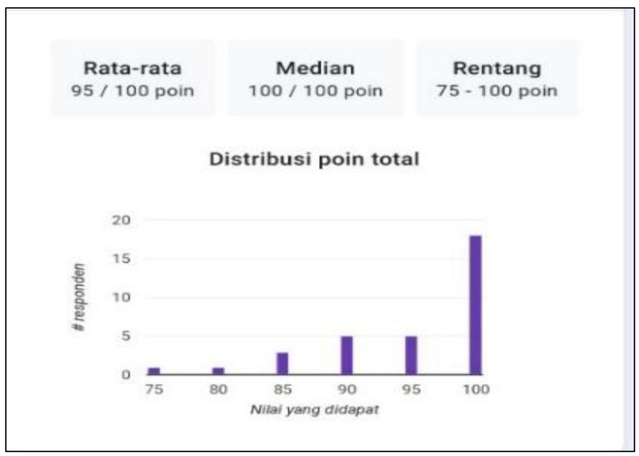


Figure. 14. Validation Test Score Results

D. Recommendation

Based on the extraction results of negative-sentiment issues, in the first issue, the government and BPJS are expected to improve the quality of healthcare services by increasing the number of medical personnel, enhancing the queueing system, improving service procedures across all classes, and upgrading hospital facilities. In addition, it is necessary to provide training for medical staff to improve service quality, strengthen monitoring mechanisms, and conduct evaluations of hospitals, clinics, or community health centers that collaborate with BPJS. At the same time, the second issue, the government has to rethink the policy of getting rid of classes and disbursement of premiums. The government must also provide transparency in the mechanisms of setting BPJS classification grades and premium rates, so that the public will know how this policy is set. Increased levels of BPJS policy and implementation monitoring is needed to avoid any potential abuse.

V. CONCLUSION

This article presents community views towards BPJS services, as expressed in the comment columns on social media news posts. Sentiment Analysis 40.6% of comments are neutral 43.9% negative 15.5% positive Proportion of positive sentiment Some customers share good experience such as quality and health in patient's care. On the contrary, negative sentiment more or less emphasises related to service medical quality, BPJS class determination and policy of payment premium. Level 4 depicts the neutral sentiment here includes, for example administrative procedures and everyday use of services provided by BPJS around technical issues like registration process, accessing services or routine communication on user side as well as rather "program specific" routine interaction with systems introduced by BPJS. It is hoped that these results wil be interesting for the government to develop various services, which often received critics and still maintain the superior quality of BPJS service that already classified as good by public. By appreciating these varied perceptions, the government can be more proactive in fulfilling users demand and expentancies of BPJS.

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