

Sentiment analysis of online licensing service quality in the energy and mineral resources sector of the Republic of Indonesia

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ABSTRACT

The Ministry of Energy and Mineral Resources of the Republic of Indonesia regularly assessed public satisfaction with its online licensing services. User rated their satisfaction at 3.42 on a scale of 4, below the organization's average of 3.53. Evaluating public service performance is crucial for quality improvement. Previous research relied solely on survey data to assess public satisfaction. This study goes further by analyzing user feedback in text form from an online licensing application to identify negative aspects of the service that need enhancement. The dataset spanned September 2019 to February 2023, with 24,112 entries. The choice of classification methods on the highest accuracy values among decision tree, random forest, naive bayes, stochastic gradient descent, logistic regression (LR), and k-nearest neighbor. The text data was converted into numerical form using CountVectorizer and term frequency-inverse document frequency (TF-IDF) techniques, along with unigrams and bigrams for dividing sentences into word segments. LR bigram CountVectorizer ranked highest with 89% for average precision, F1-score, and recall, compared to the other five classification methods. The sentiment analysis polarity level was 36.2% negative. Negative sentiment revealed expectations from the public to the ministry to improve the top three aspects: system, mechanism, and procedure; infrastructure and facilities; and service specification product types.

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1. INTRODUCTION

Since 2019, the Ministry of Energy and Mineral Resources (MEMR) has initiated digitalizing business licensing services in Indonesia's energy and mineral resource sectors. The MEMR provides risk-based business licensing services, which consists of several subsectors such as oil and natural gas, electricity, minerals and coal, new energy, renewable energy, and energy conservation through an integrated electronic business licensing system. Driven by the limitation of face-to-face services due to the impact of the COVID-19 pandemic in March 2020, the digitalization process for licensing services at the MEMR of Indonesia was further enhanced, experiencing a 700% increase in user uptake. The energy and mineral resources (EMR) sector was chosen because of the investment realization from 2019 to 2022 amounting to USD 28.45 billion, making it one of the largest investment-contributing sectors in Indonesia, and is considered stable amidst a general investment slowdown due to the pandemic and the economic growth following the pandemic.

As a public service provider, the online licensing service must conduct a community satisfaction survey periodically at least once a year. This survey is carried out periodically to obtain the community satisfaction index as a performance evaluation of the services provided to enhance the quality of public services. In the survey implementation, service recipients are asked to rate each service's importance and performance level based on nine indicators established by the Ministerial Regulation of the Ministry of State Apparatus Utilization and Bureaucratic Reform. From 2019 to 2022, the online licensing services of the MEMR achieved a community satisfaction score of 3.42, below the score of 3.53 for the directorate owning the service.

The satisfaction surveys conducted by the ministry also collect feedback in the form of appreciation, criticism, suggestions, and inputs about the services in text form filled out by users of the online-based licensing services every time they obtain or apply for benefits. However, this feedback data has not been optimally processed due to the lack of regulations on processing survey data in text form. In previous research, service quality was measured based on indicators and procedures listed in the Ministry of State Apparatus Utilization and Bureaucratic Reform number 14 of 2017 [1]. That research revealed the level of service satisfaction based on predetermined data entries and indicators, but it could not identify the complaints frequently experienced by users.

In this research, the main objectives are to determine the sentiment polarity of users of online licensing services in the EMR sector and to identify which aspects significantly impact service satisfaction levels. Sentiment analysis will be employed to evaluate the public satisfaction survey data. This method will classify the text data provided by users into positive or negative sentiment categories. The negative sentiments will be further analyzed to pinpoint the key dimensions of public satisfaction. The outcomes of this research aim to offer actionable recommendations to the MEMR for targeted improvements in public service delivery based on the issues most frequently raised by users.

2. METHOD

This subtitle delineates the foundational concepts driving this research and articulates the prevailing perspectives on implementing and evaluating information systems. It looks into different theories about using IT and explores various methods and ideas that support this study. Included are detailed descriptions of the concepts, models, research tools, methodologies for data collection, and the data processing techniques employed in this study.

2.1. Service quality and sentiment analysis

Service quality refers to the caliber of integrated interaction, information sources, and internet-based services aimed at enhancing trust in an organization [2]. It can be measured by the gap between the service users' expectations and the actual services experienced. Better service quality is indicated by a narrower gap between expectations and reality, while a wider gap signifies poorer quality [3]–[5]. Evaluating service quality is expected to bridge this gap by providing feasible solutions [6].

Based on user feedback, sentiment analysis is one method to measure the gap between expectations and perceived reality. It offers insights into public opinions, evaluations, attitudes, and emotions regarding specific objects such as products, services, organizations, individuals, issues, events, and topics [7]. Public opinion can generate either positive or negative sentiments towards a product or service [8]. Improvements can be made to the object in question to enhance public satisfaction with the services [9].

2.2. Dataset and annotations

In analyzing a text, researchers collect a dataset. A dataset is a collection of data consisting of rows and columns that describe examples of data observed using machine learning. Datasets are necessary for creating predictive models during training. The use of datasets in machine learning for classification is divided into two parts: training and testing. Generally, the proportion of training data is more prominent, about more than 70%, than the total data [10].

The collection process of user feedback is conducted at the relevant agency, with the customer satisfaction survey data originating from online licensing service applications of the MEMR, spanning from September 21, 2019, to February 8, 2023, in the form of an Excel file. The survey data entries are filled out by contact persons from the business entities using the service after obtaining the licensing services. The survey data entries include the type of company, the importance and performance values of each dimension, and feedback on the services received in the form of text.

The dataset is created by assigning labels to each data entry. Data labeling is applied to each row of data and then labeled as positive or negative [8]. This labeling is done manually by annotators. The number of annotators is more than one and an odd number to ensure objective results. During the labeling process, if

there are differing labels, the majority label is chosen. The total dataset collected is 75% of the entire available data. Five people carried out annotation and assessed positive and negative ratings.

2.3. Data pre-processing

The pre-processing stage is performed by selecting raw data and transforming it into more structured data. Pre-processing reduces irrelevant and redundant data to optimize computational datasets during the machine learning model training phase to make it faster [11]. The platform used in this process is Python, with Conda as the package and environment management systems. Data pre-processing includes cleansing, transformation, tokenization, data stemming, and stopword removal and carried out in this stage include [12]–[17]:

- Cleansing: the process removes special characters such as hashtags, URL links, ASCII characters, numbers, and HTML attributes.
- Transformation: this stage begins with converting all words to lowercase.
- Tokenization: each word in a sentence is separated one by one.
- Data stemming: removing prefixes and suffixes to obtain the root word of each word.
- Stopword removal: deleting words that are commonly used but do not significantly influence the sentence. Examples of widely found stopwords include 'dan' (and), 'atau' (or), 'dari' (from), 'itu' (that).

An example of pre-processing on one of the service satisfaction data provided by the business entity is shown in Table 1.

Table 1. Pre-processing survey sentence

Process	Result
Raw Data	Dear Mr. Director, the process of waiting 7 working days is too long, please consider speeding up the response process regarding this permit to a maximum of 2 working days. :)
Cleansing	Dear Mr Director the process of waiting working days is too long please consider speeding up the response process regarding this permit to a maximum of working days
Transformation	dear mr director the process of waiting working days is too long please consider speeding up the response process regarding this permit to a maximum of working days
Tokenizing	dear mr director the process of waiting working days is too long please consider speeding up the response process regarding this permit to a maximum of working days
Stemming	dear mr director the process of wait work day is too long please consider speed up the response process regard this permit to a maximum of work day
Stopword Removal	process wait work day too long speed up response process regard permit maximum work day

2.4. Feature extraction

Feature extraction simplifies the original data by selecting key pieces of information to create a set of characteristics, known as a feature vector. This process involves using N-grams, which break down sentences into groups of words. The 'N' in N-grams refers to the quantity of words grouped in a segment. [18]. Applying N-grams can improve the accuracy of the classification process [18]–[21]. There are three kinds of N-Gram [22]: a unigram consists of one syllable, a bigram consists of two syllables, and a trigram consists of three. The result of the extraction process uses N-grams on a sentence to obtain the most relevant information, as shown in Table 2. Next, the extracted results are converted into a numerical representation to be processed through electronic media. CountVectorizer and term frequency-inverse document frequency (TF-IDF) transform the text into a numerical representation, then processed in machine learning. CountVectorizer prioritizes the frequency of words in a document, while TF-IDF combines the frequency of words and the inverse document frequency to create an informative text vector representation [17], [23].

Table 2. N-Gram extraction result

Unigram	Bigram
Process, wait, work, day, too, long, speed, up, response, process, regard, permit, maximum, work, day	Process wait, wait work, work day, day too, too long, long speed, speed up, up response, response process, process regard, regard permit, permit maximum, maximum work, work day

2.5. Classification

Generally, there are two methods for sentiment classification: the machine learning approach and the lexicon approach. The lexicon approach utilizes a dictionary of words with positive, neutral, or negative

connotations. Meanwhile, the machine learning approach develops learning algorithms and classification models from a dataset [24]. Machine learning methods are generally categorized into supervised and unsupervised learning. Supervised learning requires substantial pre-labeled training data, whereas unsupervised learning is applied when labeling training data is impractical [25]. Standard classification methods include decision tree (DT), random forest (RF), naive bayes (NB), stochastic gradient descent (SGD), logistic regression (LR), and k-nearest neighbor (k-NN) [11], [26].

2.6. Evaluation

The classification process is followed by measuring the performance of the machine learning classification and comparing the performance and effectiveness of each evaluated method. The evaluation uses the confusion matrix, as shown in Table 3, as a decision-making method that depicts the algorithm's confusion level [27], [28]. The confusion matrix is represented using a table containing the data correctly and incorrectly classified [29] and commonly used to calculate the accuracy of data mining. The values of true positives (TP) and true negatives (TN) provide information that the classification has been done correctly. In contrast, the importance of false positives (FP) and false negatives (FN) indicates that the data classification is incorrect [30]. Based on the confusion matrix in Table 1, performance measure of precision, recall, and F1-score [12] can be calculated in (1)-(3):

$$Precision = \left(\frac{TP}{TP+FP} \right) \quad (1)$$

$$Recall = \left(\frac{TP}{TP+FN} \right) \quad (2)$$

$$F1 - score = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall} \right) \quad (3)$$

Table 3. Confusion matrix

Confusion matrix	Actual sentiment	
	Positive	Negative
Predicted positive	TP	FP
Predicted negative	FN	TN

2.7. Negative sentiment dimension

The next step is to categorize each sentiment analysis according to each dimension. Each word is taken from the data collection and grouped according to a previously defined dictionary. Fundamentally, there are five dimensions of general service quality encompassing tangible evidence, assurance, empathy, responsiveness, and reliability [31]. In addition to previous research, various studies have been developed in different contexts and industries to obtain service quality measurements in various industries [32], including e-GovQual for e-government service quality [33] and democratic e-governance website evaluation model [34].

The factors that influence the quality of online governmental services are divided into functional aspects directly related to the scope of services provided by the system and non-functional aspects related to the ease of use, operation, availability, and security of the website [35], [36]. Service mechanisms and procedures include standardized service procedures for service providers and recipients, including complaints [37]. Procedure information in this study covers general news and standard service information available on websites regarding licensing procedures [9], [38]–[40]. Facilities and infrastructure in this study refer to elements that can be activated or mobilized in the system, such as computer technology and mechanical equipment. Infrastructure, on the other hand, refers to the foundational elements of the system, such as physical facilities and infrastructure.

The annotators compile a data dictionary, grouping words by each dimension derived from the survey responses. This reference tool is then employed to track the frequency of phrases categorized under negative sentiments, breaking down the counts according to respective service dimensions. The approach to defining service quality dimensions encompasses several steps: initially, each aspect of service quality is extracted from the analysis of sentences containing the categorized terms. This classification focuses exclusively on negative sentiments. The frequency of each grouped term is quantified and subsequently scrutinized concerning the most pertinent factor. If the context of the complaint is not clear from the word alone, the surrounding words—preceding or following—are considered to achieve a more precise interpretation. Ultimately, these calculated frequencies aid in pinpointing the factors influencing customer satisfaction with the service.

Table 6. Classification results

String extraction	Classifier	Confusion matrix	CountVectorizer		TF-IDF	
			Negative	Positive	Negative	Positive
Unigram	k-NN	Negative	543	1240	187	1596
		Positive	106	2952	54	3004
	LR	Negative	1393	390	1422	361
		Positive	244	2814	262	2796
	NB	Negative	1392	391	1314	469
		Positive	318	2740	256	2802
	RF	Negative	1403	380	1482	301
		Positive	285	2773	324	2734
	DT	Negative	1286	497	1291	492
		Positive	452	2606	448	2610
	SGD	Negative	1423	360	1475	308
		Positive	276	2782	287	2771
Bigram	k-NN	Negative	358	1425	59	1724
		Positive	88	2970	8	3040
	LR	Negative	1451	332	1402	381
		Positive	210	2848	239	2819
	NB	Negative	1406	377	1173	610
		Positive	306	2752	146	2912
	RF	Negative	1337	446	1452	331
		Positive	268	2790	267	2791
	DT	Negative	1299	484	1324	459
		Positive	424	2634	446	2612
	SGD	Negative	1370	413	1469	314
		Positive	252	2806	243	2815

3.4. Evaluation

Precision, recall, and F1-score for each classification are calculated to correct the classification values mentioned [12]. Table 7 displays the results of these evaluations. These metrics help in understanding the performance of each classifier by providing details on the accuracy of the optimistic predictions (precision), the ability to find all the positive instances (recall), and a balance between precision and recall (F1-score), especially when dealing with imbalanced datasets. The comparison of each method using the confusion matrix in Table 7 indicates that bigram LR achieved the highest F1-score (89%). The F1-score is based on an imbalanced dataset between positive and negative classes. Based on these results, LR is chosen as the predictive model for the next steps. The sentiment analysis results using bigram CountVectorizer LR show that positive sentiments account for a more significant percentage, precisely 63.2%, compared to negative sentiments, which constitute 36.8%.

Table 7. Evaluation results

String algorithm	Classifier	CountVectorizer			Tf-Idf		
		Precision	Recall	F1-score	Precision	Recall	F1-score
Unigram	k-NN	0.75	0.72	0.68	0.70	0.66	0.56
	LR	0.87	0.87	0.87	0.87	0.87	0.87
	NB	0.85	0.85	0.85	0.85	0.85	0.85
	RF	0.86	0.86	0.86	0.87	0.87	0.87
	DT	0.8	0.8	0.8	0.8	0.81	0.81
	SGD	0.87	0.87	0.87	0.88	0.88	0.88
Bigram	k-NN	0.72	0.69	0.62	0.69	0.64	0.51
	LR	0.89	0.89	0.89	0.87	0.87	0.87
	NB	0.86	0.86	0.86	0.85	0.84	0.84
	RF	0.85	0.85	0.85	0.88	0.88	0.88
	DT	0.81	0.81	0.81	0.81	0.81	0.81
	SGD	0.86	0.86	0.86	0.88	0.88	0.88

3.5. Negative sentiment dimension

The researchers established a dictionary for each predetermined service quality dimension. The five annotators carry out the dictionary based on the dimensions of service quality, considering all the survey data available. Using the service quality dimension dictionary and the negative sentiment data, the researchers conducted data crawling and comparing the data dictionary and the survey responses previously filled out by respondents. Among the nine predetermined dimensions, the system, mechanism, and procedure dimensions dominate with a total of 4,487 negative sentiments from the overall negative sentiments expressed by service

users. Table 8 shows the mapping results between service quality dimensions, dictionary, and total negative sentiment.

Table 8. Dictionary of service quality dimension

Service quality dimension	Dictionary	Total negative sentiment	Highest word frequency
System, mechanism, and procedure	Guide, manual, mentor, socialization, register, example, reject, track, monitor, workflow, standard, government, draft, list, issue, evaluation, note, review, approve, validation, revision, tutorial, meet, process	4487	Process (1385)
Infrastructure and facilities	Browser, upload, show, file, chrome, firefox, download, access, integration, login, submit, feature, zip, limit, coordinate, error, character, connection, network, server, scroll, website, response, notification, chat, online, offline, synchronize, capacity	3789	Upload (1045)
Product specification of service type	Services, mining license (IUP) (<i>izin usaha pertambangan</i>) (IUP), minerba one data Indonesia (MODI), minerba one map Indonesia (MOMI), trade, transportation, import, online single submission (OSS), storage, warehouse, geothermal, fuel, new, extension, amendment, business license for supplying electricity (IUPTL) (<i>izin usaha penyediaan tenaga listrik</i>) (IUPTL), recommendation, mining business permit area (WIUP) (<i>wilayah izin usaha pertambangan</i>) (WIUP), ownership, Capital Investment Coordinating Board (BKPM) (<i>Badan Koordinasi Penanaman Modal</i>) (BKPM)	3197	IUP (853)
Requirements	Regulation, requirement, criteria, provision, condition, prerequisite, parameter, reference, demand, compliance, document, field	2462	Document (1022)
Completion time	Duration, length, period, speed, service-level agreement (SLA), time	1085	Time (730)
Handling of complaints, suggestions, and feedback	Response, action, acceptance, record, feedback, analysis, operator, follow, solution, supervision, report, management, RPIT, helpdesk, impact, contact, satisfaction	236	Response (91)
Executor's behavior	Attitude, professionalism, friendly, communication, discipline, cooperation, reliability, responsibility, responsive	186	Responsive (82)
Cost/tariff	Fee, price, charge, bill, invoice, payment, levy, surcharge	138	Payment (82)
Executor's competence	Ability, expertise, implementation, executor, performance, effectiveness	45	Executor (23)

The analysis identified three dimensions with the highest total negative sentiment based on word frequency. This prioritizes them for service improvement. The word frequency is linked with a word before or after to pinpoint more specific issues. In the dimensions of system, mechanism, and procedure, it was found that there is a need for a process evaluation of permits to ensure compliance with current rules and standard operating procedures. Additionally, there are processes related to integrated permits that businesses do not understand well. This issue necessitates socialization to business entities using the service about the service process through the application, both for internal ministry permits and those integrated with other ministries, providing easily understandable guidelines for users. Furthermore, an internal audit by the MEMR is expected to simplify the submission process and speed up the permit evaluation process.

The limitation in file format and size during the file upload process contributed the most to negative sentiment in the dimension of facilities and infrastructure, followed by difficulties filling out map coordinates and project locations. To address these issues, the ministry could implement a feature for validating file inputs, enhance the system's capacity to handle larger files according to user needs, and allow users more time to upload bigger files. Moreover, integration with the EMR single map service through Geoportal could simplify the process of filling out map coordinates, accompanied by a comprehensive user guide.

Finally, in the dimension of product service specifications, it was found that the IUP permit type received the highest frequency of negative sentiment, followed by OSS permits and WIUP permits, which were frequently mentioned in complaints. An internal audit could be conducted for these three types of services to optimize the application and business process. These findings suggest a need for targeted improvements in specific areas to enhance service efficiency and reduce negative sentiment among users. Furthermore, providing comprehensive integrated guidelines and strengthening the function of the contact center would be very helpful.

4. CONCLUSION

This research presents an analysis of user sentiment from an online licensing service in the EMR sector, starting with the creation of a training dataset to build a predictive model. The process of developing the predictive model began with data transformation, which included steps like transformation, tokenization, stemming, and removing stopwords, followed by data classification to determine the most suitable predictive model for the case study. The bigram LR model emerged as the most accurate, with the best precision and

recall rates. An analysis of data from 4,600 companies within the sector yielded 24,412 responses from a public satisfaction survey, which were categorized into nine dimensions. From these responses, 36.8% expressed negative sentiments toward the service received, with the highest number of negative sentiments directed at the system, mechanism, and procedure, while the competency of implementers was the least criticized aspect. This research suggests that future studies could explore other variables, such as the correlation between service satisfaction levels and investment levels, and expand the scope to include more areas relevant to the Ministry of State Apparatus Utilization and Bureaucratic Reform, especially concerning public satisfaction surveys and their impact on online services.

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