Evaluation of user satisfaction in the public sector's Lelang Indonesia application using sentiment analysis and text mining

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Abstract

The increasing adoption of mobile applications in public service delivery has brought both opportunities and challenges in evaluating service quality. This study investigates user perceptions of the Lelang Indonesia mobile application, administered by the Directorate General of State Assets Management, Ministry of Finance, by analyzing 682 user reviews collected from the Google Play Store over the past six years. Sentiment analysis was conducted by manually categorizing review scores into positive and negative sentiments, followed by classification using the Support Vector Machine (SVM) technique to assess model accuracy. In addition, text mining techniques were applied to identify recurrent issues and concerns highlighted by users. The results indicate that many users encounter significant barriers, primarily related to technical functionality and service procedures, which negatively impact their assessment of public service quality. These findings underscore the need for continuous monitoring and improvement of mobile-based public services. The study provides actionable insights for public institutions to proactively enhance auction service quality and demonstrates the value of real-time sentiment analysis for evaluating public satisfaction with digital government platforms.

Keywords*: mobile application, public sector, sentiment analysis, text mining, lelang indonesia.*

Introduction

The advancement of information and communication technology, particularly with the advent of the internet, is a significant catalyst for transformations in public services (Scavo, 2003). The internet enables the public to engage more profoundly with the government in expressing their concerns (King & Brown, 2007). This ethos aligns with the concept articulated by Osborne and Gaebler (1992) in "Reinventing Government," which necessitates that public institutions consistently monitor, analyze, and measure as a foundation for ongoing enhancement. Public institutions presently offer services that enhance accessibility and proximity to the community via internet-based platforms and mobile applications Lee (2024) One public service that uses internet technology and mobile applications in Indonesia is the Indonesian auction service (Lelang Indonesia), administered by the Directorate General of State Assets Management (DGSAM), Ministry of Finance.

Auction services facilitate the purchase and selling of goods, including real estate, vehicles, electronics, timber, metal, and other MSME products, conducted by the government. Initially, the service was conventional, with state auction officials selecting bidders with the highest price bids in person at a designated location and time. However, beginning in 2014, the advent of internet technology enabled bidders to submit auction bids easier, faster, efficiently, and securely using their respective devices (Bandiyono &

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Muttaqin, 2020). The auction service is accessible to the public via the “lelang.go.id” website or the Android-based mobile application named “Lelang Indonesia”, available for download on the Google Play Store.

Ganapati (2015) asserted that mobile application-based public services are citizen-centric applications and must be compatible with the diverse devices frequently utilized by citizens. These applications enable "anytime, anywhere" citizen participation (e.g., via crowdsourcing and social media) with governmental entities for innovative services and decision-making processes. Applications generally employ information accessible via public agency data repositories. Government data is a crucial element for enhancing public services.

Certain public services are obligated to follow the existing regulations. However, Sharma et al. (2018) conducted a study and found that elements such as performance expectations, effort expectations, supporting environment, trust, and information quality significantly impact the public's decision to utilize government mobile applications. Mobile applications are considered one of the channels that allow individuals to interact with government services without time and location constraints (Sharma et al., 2018). The availability of mobile applications enables individuals to effortlessly submit reviews and report a variety of issues, including bug reports, feature requests, user experience feedback, and ratings, which developers of mobile applications must consider with utmost care (Maalej & Nabil, 2015).

The written text generated by an individual can offer insights from multiple perspectives, including comprehension of individuals and their behaviors in connection to other entities (Berger et al., 2020). In the digital era, the vast amount of content generated from ever-increasing internet and online activities has opened a new direction for communication through unstructured text (e.g., chatting, blogs, reviews, social media content, e-commerce, and online banking) (Chauhan et al., 2023).

Text mining is a type of big data analysis that employs tools to extract data from extensive collections of documents containing textual content, such as journal articles, social media posts, advertising, product reviews, or customer emails (Mills, 2019). Text mining aims to extract implicit knowledge from unstructured textual data, which comprises a sequence of words (Jo, 2019). Text mining transforms unstructured textual input into a format as informative as structured data, enabling the identification of patterns and relationships that were previously challenging to do (Zanini & Dhawan, 2015).

Sentiment analysis, also known as opinion mining, involves the examination of individuals' opinions, sentiments, evaluations, ratings, attitudes, and emotions toward entities such as products, services, organizations, individuals, situations, events, themes, and their attributes (Liu, 2012). Sentiment analysis determines the polarity of thoughts in a text, categorizing them as positive, negative, or neutral (Magtangob & Palaoag, 2023). A positive sentiment indicates favorable feelings toward an entity, whereas a negative sentiment reflects unfavorable feelings (Prior et al., 2024).

Riaz et al. (2019) asserted that sentiment analysis relies not only on the tools used but also necessitates human intelligence due to the following factors: 1) data must be organized, 2) customer opinions often exhibit bias in star ratings, 3) textual feedback must be scrutinized to yield clearer insights, 4) textual feedback necessitates Natural Language Processing (NLP), and 5) human expertise is essential, particularly for executing manual evaluation processes.

Sentiment analysis is frequently utilized across diverse domains. It is used mainly for 1) decision-making assistance (notably in generating innovative business concepts), 2) business applications (including the assessment of products and services), and 3) trend analysis (leveraging sentiment to identify market trends) (Mehta & Pandya, 2020).

Hutto and Gilbert (2014) discussed that sentiment analysis can be conducted using machine learning and lexicon-based approaches. Machine learning-based approaches can be executed through supervised or unsupervised learning by researchers, whereas lexicon-based approaches rely on various dictionaries of terms generated in line with the relevant language (Medhat et al., 2014).

Analyzing user reviews and utilizing them for enhancement is crucial because it can significantly impact the download and use of mobile applications by users (Liang et al., 2015). As negative reviews are collected without a substantial response from the mobile application provider, user engagement with the application would likely diminish significantly. Consequently, research pertaining to the identification and sentiment analysis of user reviews is crucial for the evaluation of services Kim and Hong (2020) and can forecast customer or user sentiment Borg and Boldt (2020) as a basis for ongoing enhancement.

Nevertheless, it has not been a significant concern for public sector entities. Evaluations in the public sector are still performed by a limited group of specialists utilizing surveys (Kim & Hong, 2020). Furthermore, the scarcity of research concerning public service evaluation via sentiment analysis for public sector services is evident. The majority of sentiment analysis research is performed in the private sector, particularly concerning items and services within the e-commerce domain (Hawlader et al., 2021; Yang et al., 2020), tourism and hospitality services (Abbasi-Moud et al., 2021; Jardim & Mora, 2021), transportation and aviation services (Kiliç & Çadirci, 2022; Patel et al., 2022), and banking services (Adiningtyas & Auliani, 2024; Agoraki et al., 2022). Nevertheless, the public increasingly insists that governments regard individuals as 'customers' and provide more interactive, prompt, and customized services (Chhabra & Kumar, 2009).

Kim and Hong (2020) Studies on text mining analysis concerning public sector services were conducted to evaluate the service quality of public bicycle-sharing systems in South Korea. The research utilized data from Twitter and customer reviews posted on the bicycle-sharing service provider's website, employing a deep learning-based sentiment analysis technique. The study's findings indicated that identifying positive and negative elements influencing service quality through the analysis of user feedback can enhance public bicycle-sharing systems in South Korea.

Ramzy and Ibrahim (2024) studies on sentiment analysis pertaining to public service mobile applications focused on 18 Arabic-language COVID-19 mobile applications. The research utilized a dataset obtained from Google Play Store evaluations and subsequently examined it employing several machine learning-based sentiment analysis techniques. The study's findings indicate that machine learning-based sentiment analysis has high predictive accuracy and effectively assesses the service user satisfaction levels among mobile application users.

Despite the advancement in the study of sentiment analysis, there remains a gap in understanding fundamental review topics presented by users, which form the basis of their review narratives derived from their experiences. Previous research has mostly focused on sentiment analysis techniques and their effectiveness in predicting user sentiment, often neglecting the main review topics articulated by users. This study seeks to address the gap by examining the main review subjects expressed by users, specifically those of the Lelang Indonesia mobile application, through the application of diverse text mining algorithms.

The novelty of this study is demonstrated through the integration of sentiment analysis methods with text mining algorithms to discern sentiment from reviews by public service users in Indonesia, while concurrently identifying the primary topics behind users' reviews. This study provides novel perspectives on assessing public service user satisfaction in Indonesia, especially through real-time evaluations as a proactive measure that public institutions can implement to enhance services in accordance with user expectations and aspirations.

This research offers two unique additions to the field of sentiment analysis. This study utilizes the sentiment analysis model created by Ramzy and Ibrahim (2024) while including additional text-mining approaches to better understand the primay issues by examining relevant words and phrases. This study's objective closely parallels the research conducted by Kim and Hong (2020), which aims to evaluate public service satisfaction and offer valuable ideas for enhancing these services. Nonetheless, there are distinctions in the study, specifically on the sentiment analysis methodology and the data sources employed. This study additionally assesses the performance of the constructed model, which was not addressed in Kim and Hong (2020) study. This study has three primary objectives:

1. To ascertain the sentiment of users of the Lelang Indonesia mobile application based on the reviews they submit through the Google Play Store ratings and reviews feature, using a machine learning-based sentiment analysis (the SVM).
2. To identify the main topic of reviews submitted by users of the Lelang Indonesia mobile application.
3. To offer an alternate approach for the rapid or real-time and efficient evaluation of public services by institutions, yielding significant information for ongoing service enhancements aligned with user expectations.

Methods

This study employed the sentiment analysis methodology established by Ramzy and Ibrahim (2024) and incorporated additional text-mining techniques to analyze the primary subjects following model construction. The study procedures were illustrated using a flowchart, as depicted in figure 1. The particulars of each scenario are explained here.

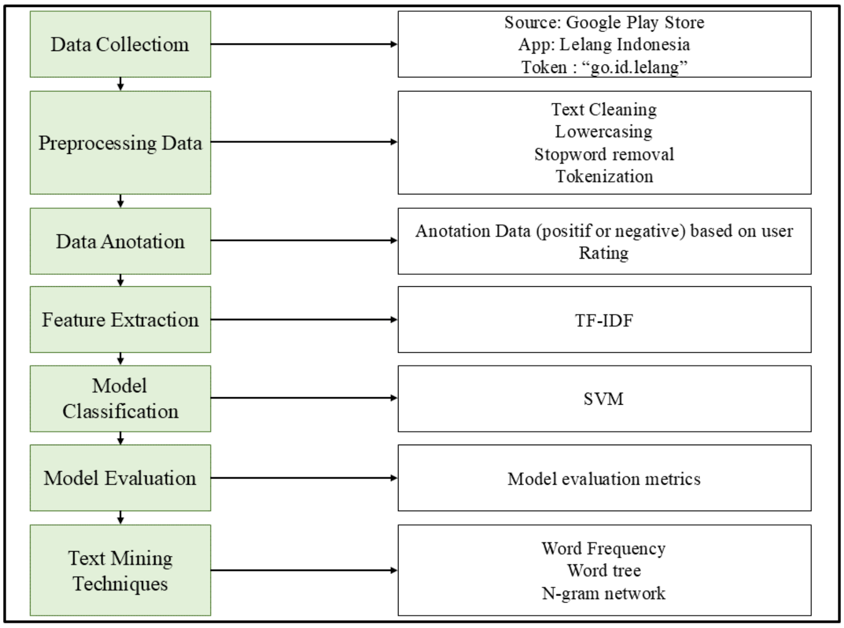

Figure 1. Methodological Procedures

This study utilized a dataset of reviews for the Lelang Indonesia mobile application obtained from the Google Play Store. The data scraping method performed the google-play-scraper library on August 20, 2024. This review data scraping utilized the token 'go.id.lelang'. The obtained data comprised 682 review comments with diverse ratings. The retrieved data comprises user name, timestamp, star rating, and review comments, stored in a Comma Separated Values format and subsequently transformed into Microsoft Office Excel File Format.

Data sourced from databases or the internet is occasionally unstructured and disorganized (Berger et al., 2020). Consequently, a data preprocessing phase was necessary, which involved cleaning and preparing text for categorization for subsequent analysis (Haddi et al., 2013). The data preprocessing phase was crucial, as testing a model with inadequately prepared data can yield incorrect information and inadequate performance. The quality of data will decline in the presence of excessive irrelevant information or data noise. Comprehending and employing suitable preprocessing methods for each case study was essential for acquiring high-quality data (Isnan et al., 2023). The subsequent details pertained to the stages of data preprocessing as follows:

1) Text cleaning, is the act of eliminating words, symbols, or emojis commonly present in internet content, including URLs, HTML, and tags (Zucco et al., 2020). Furthermore, this method can eliminate some spaces or deceptive characters, such as excessive punctuation, which, if not addressed, may lead to biased information (Chiny et al., 2021); 2) Lowercasing, commonly referred to as case folding, is a technique for converting all characters in a dataset to lowercase. This is executed to streamline the dataset analysis process and minimize memory consumption (Mustaqim et al., 2020); 3) Stopword removal, entails the elimination of coordinating conjunctions, such as for, not, or, still, so, and prepositions, including in, beneath, against, before, and after (Zucco et al., 2020). These words typically co-occur with the primary words, rendering them non-unique and have no special meaning. A compilation of terms that offer minimal value to analytical material is referred to as stopwords or a

stoplist (Mustaqim et al., 2020); and 4) Tokenization, the procedure of segmenting text into smaller units known as tokens, determined by spaces or punctuation (Jo, 2019). Although most text mining or sentiment analysis software has sophisticated tokenization capabilities, researchers must remain vigilant regarding particular instances of textual corpora (Berger et al., 2020).

This study employed manual data annotation, using a rating score to assign positive, neutral, and negative labels. This study's manual data labeling is based on research by Ramzy and Ibrahim (2024), which establishes sentiment labeling criteria: user star ratings of 1-2 stars indicate negative sentiment, 3 stars denote neutral emotion, and 4-5 stars signify positive sentiment. In evaluating user happiness, this study removed data categorized as "Neutral" based on the results of the data labeling conducted. A study by Kim and Hong (2020) indicated that the "Neutral" category fails to represent both customer satisfaction and dissatisfaction. A study by Alhaqq et al., (2022) established a rating system where a score of 1 indicates very poor, 2 indicates poor, 4 indicates good, and 5 indicates very good.

In sentiment analysis, researchers must conduct a weighting calculation for each word (extraction) based on its uniqueness or frequency of occurrence before executing text classification or constructing models with machine learning algorithms. This study employed feature or word extraction through the term frequency-inverse document frequency (TF-IDF) method in this research. Term frequency (TF) quantifies the frequency of a word within a document, whereas inverse document frequency (IDF) assesses the significance of a word by determining its inverse frequency across all documents; a word that appears in numerous documents yields a lower IDF value, indicating reduced specificity or importance (Jo, 2019).

The TF-IDF formulation is articulated through various equations, detailed as follows: Equation (1) delineates the TF calculation, where TF (t,d) represents the frequency of term t in document d, N (t,d) signifies the count of term t within document d, and T denotes the total number of words in the document. For example, if the document d contains the following text: “memudahkan dalam pengajuan proses lelang (it makes it easier to submit the auction process)”, then N (“lelang”, d) = 1, because the word “lelang (auction)” appears once in the document d and T = 5 (total number number of words in the document). Equation (2) delineates the IDF computation, wherein IDF (t) indicates the rarity of word frequency inside the document, N represents the total number of documents, and N (t) signifies the count of documents that include word t. Equation (3) represents the calculation of Term Frequency (TF) and Inverse Document Frequency (IDF) utilized for determining TF-IDF (Chiny et al., 2021).

$$TF\ (t,d) = \frac{N\ (t,d)}{T} \qquad (1)$$

$$IDF\ (t) = \frac{Log\ N}{(N\ (t))} \qquad (2)$$

$$TF - IDF = TF * IDF \qquad (3)$$

A higher TF-IDF score signifies that a phrase is significant to the document and comparatively infrequent across other documents, suggesting that the word is crucial for effectively summarizing the document (Riaz et al., 2019). The TF-IDF algorithm is a widely utilized feature weighting method in sentiment analysis due to the efficacy of TF-IDF in accurately classifying sentiment (Chiny et al., 2021; Jo, 2019; Liu, 2012).

Model Classification

A classification model utilizing a machine learning method, specifically the Support Vector Machine (SVM) Model, was executed at this stage. The support vector machine (SVM) is a supervised learning method that analyzes data and identifies patterns for text classification (Basari et al., 2013). The SVM is employed to predict classifications based on the formats or patterns derived from the training and testing procedures (Waspodo et al., 2022).

This technique uses kernels to transform data into a higher-dimensional space to classify non-linearly separable data. Kernels necessitate the utilization of a set of adjustable parameters, referred to as hyperparameters (Isnan et al., 2023). The SVM is a widely utilized method for text classification, particularly in sentiment analysis domains (Kristiyanti et al., 2019). Researchers extensively utilize this technique due to its capacity to manage substantial data volumes, few hyperparameters, theoretical assurances, and exceptional practical performance (Sangeetha & Kumaran, 2022). The value of the SVM approach is in its generalization capability, enabling it to categorize data not included in the training set used for machine learning (Saikin et al., 2021).

The SVM model was trained on reviews using sentiment polarity scores derived from human-annotated sentiments. Since classification models necessitate training data within the dataset Srivastava et al. (2022), this study allocated 80% of the reviews for training and the remaining 20% for testing in our trials.

An approach to evaluating the model was to utilize a confusion matrix. The confusion matrix is commonly used to evaluate accuracy in data mining methodologies. A confusion matrix is shown by a table that delineates the quantity of accurately classified test data alongside the quantity of inaccurately classified test data. Accurate measurement can be achieved by computing the accuracy, recall, precision, and F1-score.

The criteria for assessing the quality and efficacy of the model are delineated as follows (Borg & Boldt, 2020; Ernawati et al., 2019):

a) The accuracy value serves as the primary metric for model selection, computed using the following equation:

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}$$

b) Recall or sensitivity refers to the proportion of outcomes derived from the matrix. The recall value is determined by the equation:

$$\text{Recall} = \frac{(\text{TP})}{(\text{TP} + \text{FN})}$$

c) The precision or prediction of positive values refers to the ratio of total true positives to the total number of positive responses. The precision value is determined using the equation:

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP} + \text{FP})}$$

d) The F1-Score is a metric for evaluating the effectiveness of a classification model, reflecting the harmonic mean of Precision and Recall. This metric is especially valuable when there exists an imbalance between positive and negative classes in the data, as determined by the following equation:

$$\text{F1} - \text{Score} = 2 * \frac{\text{Precision} * Recall}{\text{Precision} + Recall}$$

All parameters derived from the calculation will be detailed in the Confusion Matrix presented in table 1.

Table 1. Confusion Matrix

	Actual Value	
Prediction Value	True Positive (TP)	False Positive (FP)
	False Negative (FN)	True Negative (TN)

Furthermore, this study used an analytical instrument known as a Receiver Operating Characteristic (ROC) curve to assess the model more thoroughly. The ROC curve is a method for displaying, organizing, and selecting classifiers, particularly in sentiment analysis, based on their performance metrics (Gorunescu, 2011). The ROC curve is a two-dimensional graph depicting the false positive rate on the horizontal axis and the true positive rate on the vertical axis. To evaluate the classification accuracy of the model illustrated in the ROC curve, one must examine the area under the ROC curve (AUC) according to the rules provided by Gorunescu (2011) as follows:

0,90 – 1,00: excellent classification;
0,80 – 0,90: good classification;
0,70 – 0,80: fair classification;
0,60 – 0,70: poor classification; and
0,50 – 0,60: failure

This study employed several text-mining approaches to deepen the issues or subjects expressed by users in their reviews, enabling these insights to be examined and handled by the institution, particularly in enhancing service quality. This study used the following text-mining techniques: a) Most words frequency table, this table illustrated the facts regarding the frequency of words most commonly contributed by users. The most frequent terms will be displayed for both positive and negative emotion categories; b) Word tree diagrams, the analysis of word tree diagrams was performed to comprehend language usage concerning a specific subject. This method facilitated the acquisition of detailed insights into the cause-and-effect relationships between positive and negative words and offers alternatives for a thorough examination of a particular issue (Kim & Hong, 2020); and c) N-gram network, refers to a sequence of sorted words in a text, with n indicating the quantity of words in the sequence. If N equals 1, the text comprises a solitary word (unigram). If N is equal to 2, the text denotes a pair of sorted words (bigram) (Srivastava et al., 2022). An N-gram network described the interconnections between individual N-grams, particularly words or phrases that often occur within a document.

Result and Discussions

Data extraction from user reviews of the Lelang Indonesia Application on the Google Play Store during the past six years yielded 682 review entries. The number of reviews collected is much smaller compared to the study conducted by Alhaqq et al. (2022), which gathered 4,778 reviews from users of the MySAPK BKN mobile app over a four-year period (2017 to 2021). This is considering that the number of users of the MySAPK BKN mobile app is much larger (over one million users) compared to the users of the Lelang Indonesia mobile app (over one hundred thousand users). Table 2 illustrates the distribution of review data based on user ratings.

Table *2*. Quantity and Proportion of User Rating

Rating	Count of Users	Percentage
1	329	48%
2	35	5%
3	26	4%
4	35	5%
5	257	38%
Total	682	100%

Source: Extracted from Google Play Store (2024)

The gathered data underwent preprocessing through four stages: text cleaning, lowercasing, stopword elimination, and tokenization. Table 3 illustrates the outcomes of data preprocessing. The tokens produced from this data preprocessing serve as the foundation for feature weighting to identify the most significant words in calculating sentiment polarity (positive/negative).

Table 3. Illustration of Data Preprocessing Results

Phase	Results	
	Bahasa Indonesia	English Translation
User Review	*1. Setelah upgrade lebih susah 2. Downgrade ini nama nya 3. U/buka aplikasi masuk saja tertulis halaman tidak di temukan.*	*1. More difficult after upgrade 2. this name is Downgrade 3. U/opening the login application the message shown is page not found*
Text Cleaning	*Setelah upgrade lebih susah Downgrade ini nama nya buka aplikasi masuk saja tertulis halaman tidak di temukan*	*After upgrade more difficult this name is Downgrade opening the login application the message shown is page not found*
Lowercasing	*setelah upgrade lebih susah downgrade ini nama nya buka aplikasi masuk saja tertulis halaman tidak di temukan*	*after upgrade more difficult this name is downgrade opening the login application the message shown is page not found*
Stopword Removal	*upgrade susah downgrade nama buka aplikasi masuk tertulis halaman temukan*	*Upgrade difficult name downgrade open application login message page found*
Tokenization	*['upgrade', 'susah', 'downgrade', 'nama', 'buka', 'aplikasi', 'masuk', 'tertulis', 'halaman', 'temukan']*	*['upgrade', 'difficult', 'downgrade', 'name', 'open', 'application', 'login', 'message', 'page', 'found']*

Sentiment data annotation was then performed manually based on the rating score provided by the user in the review. Sentiment was classified into two categories: 1) positive sentiment for reviews rated 4 (good) and 5 (very good); and 2) negative sentiment for reviews rated 1 (very bad) and 2 (bad).

Twenty-six reviews, each with a rating score of 3, indicative of neutral emotion, were excluded from further analysis in the model, as they do not accurately represent customer satisfaction or dissatisfaction. The omission of 26 neutral review entries resulted in a total of 656 user reviews processed in the sentiment analysis model.

The diagram in figure 2 illustrates the quantity and proportion of the two sentiment categories (positive/negative) of the rating scores in the user reviews.

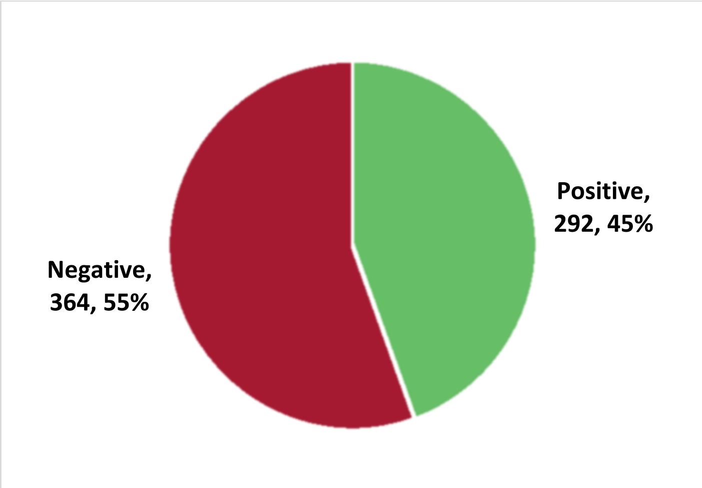

Figure 2. Distribution of Sentiment Categories

Following categorizing the data into two classifications (positive/negative), the study developed a sentiment classification model. Before constructing the sentiment model, this study used the TF-IDF technique for feature extraction or weighting to ascertain the frequency of words or word combinations that occur sufficiently often to establish sentiment polarity. TF-IDF allocates numerical values to terms according to their frequency within a document. The numerical output of TF-IDF feature weighting will serve as input for constructing a sentiment analysis model utilizing machine learning algorithms.

This study employed the SVM algorithm, recognized as a prominent method for classification and regression in both linear and non-linear contexts (Haddi et al., 2013). The SVM can autonomously identify the most pertinent features for classification by assigning greater weights to significant characteristics (words) that differentiate emotion categories while also efficiently eliminating irrelevant or redundant terms (Isnan et al., 2023). The SVM are typically employed for sentiment analysis of textual data that express opinions, emotions, or assessments derived from social media, product reviews, opinion pieces, discussion forums, customer service communications, and interview transcripts.

This study used the SVM approach to categorize sentiment analysis models, utilizing 80% of the total dataset (N = 524) as training data to develop a sentiment prediction model. This training data was utilized to assess the predictive outcomes generated by the classification model. The remaining 20% is allocated as test data (N =132). Based on the tests that were conducted, the assessment findings of the classification model in this study are presented in table 4.

Table 4. The SVM Model Classification Results

	Accuracy	Recall	Precision	F1-Score
The SVM	0,85	0,81	0,96	0,88

The model performed well, with an accuracy of 0.85 and an F1-score of 84%. The model accurately predicted the correct class in 85% of instances. The confusion matrix depicted in figure 3 provides a more detailed analysis of the model's performance. This confusion matrix will provide the model's predictions for each class and illustrate the errors committed by the model.

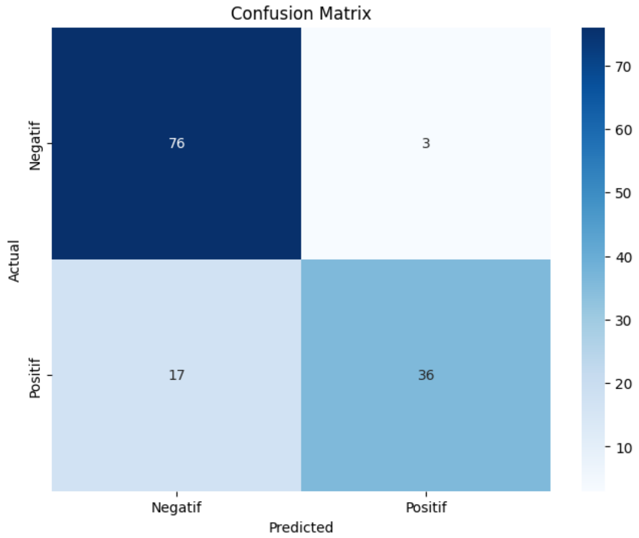

Figure 3. Confusion Matrix Diagram

The confusion matrix data depicted in figure 3 can be interpreted as follows: a) True Positive (TP): The count of genuinely positive samples accurately forecasted as positive (N = 36); b) True Negative (TN): The count of genuinely negative samples accurately forecasted as negative (N = 76); c) False Positive (FP): The quantity of genuinely negative samples classified as positive (N = 3). This error may also be termed a false alarm; and d) False Negative (FN): The count of genuinely positive samples while anticipated as negative (N = 17). This error may also be termed misclassification.

Upon reflection, the SVM classification model accurately predicts 112 out of 132 user reviews utilized as test data. The 112 review data comprises 36 reviews with positive sentiment and 76 reviews with negative sentiment. The model has an error in predicting 20 customer reviews with details of 3 reviews with positive sentiment and 17 reviews with negative sentiment. As indicated by the confusion matrix, a significant limitation of this approach is the elevated incidence of misclassifications, demonstrating that it continues to overlook several positive classes.

The model's performance can be more fully illustrated using the ROC curve depicted in figure 4. The ROC curve produced by the model is situated toward the upper left corner of the graph, signifying the model's exceptional performance. This indicates that the model can accurately classify positive samples (high actual positive rate) while minimizing wrong classifications of negative samples (low false positive rate). The model's success is evidenced by an area under the curve (AUC) value of 0.94 (getting closer to 1). The results indicate that the model effectively differentiates between positive and negative evaluations, enabling accurate sentiment identification, which is beneficial for comprehending user impressions of the Lelang Indonesia mobile application.

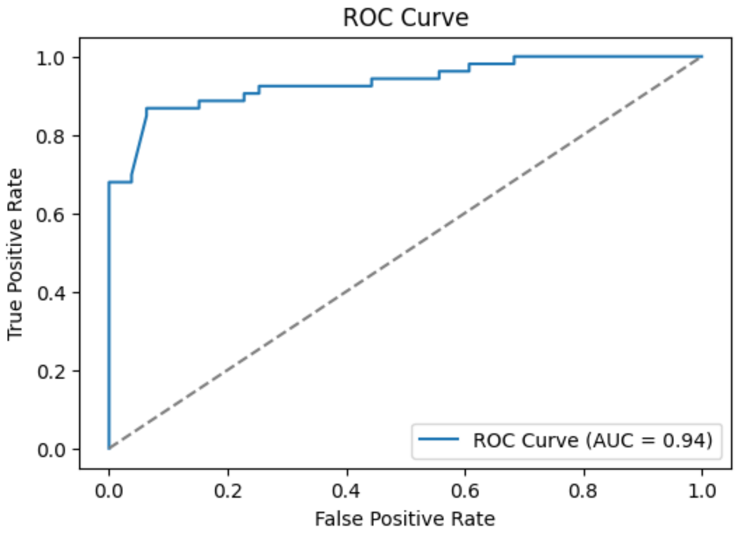

Figure 4. ROC Curve

Analysis of 656 user reviews for the Lelang Indonesia mobile application revealed that more users expressed unfavorable sentiments (55%) compared to those who articulated favorable sentiments (45%). The outcomes of the sentiment analysis will be illustrated by several analytical and visualization methods in text mining as follows:

Word Frequency Table

The top word frequency table shows the rationale for the favorable customer ratings, as shown in table 5. The top word frequency graph revealed 15 frequently occurring terms/words, including "mantap (great)", "ok (ok)", "bagus (good)", “good (good)”, and "keren (cool)" which signify a high degree of customer satisfaction with the services offered by the mobile application.

Table 5. Top 15 Words in Positive Sentiment

Rank	Term/Word	Frequency
1	“lelang (auction)”	55
2	“mantap (great)”	47
3	“ok (ok)”	35
4	“bagus (good)”	29
5	“membantu (helpful)”	21
6	“aplikasi (application)”	18
7	“good (good)”	18
8	“nan (nan)”	15
9	“Indonesia (indonesia)”	9
10	“keren (cool)”	9
11	“djkn (dgsam)”	9
12	“oke (ok)”	9
13	“mudah (easy)”	7
14	“semoga (hope)”	7
15	“barang (item)”	7

Furthermore, terms like "membantu (helpful)" and "mudah (easy)" suggest that this mobile application offers convenience to specific customers in accessing auction services that align with their expectations. Users also express their expectations with the term "semoga (hopefully)".

Conversely, the frequency table of the most used terms shows the rationale behind the negative customer evaluations, as illustrated in Table 8. The quantity of words in reviews exhibiting negative sentiment was more than that in reviews displaying positive emotion, as indicated by the sentiment distribution in the data labeling.

Table 6 reveals commonly appearing terms, such as "buruk (bad)" which signifies a diminished degree of customer satisfaction with the services offered by the mobile application. Furthermore, terms like "susah (difficult)" suggest that for certain users, this mobile application complicates their experience and induces uncertainty, preventing them from obtaining auction services that align with their expectations.

In the negatively reviewed feedback, consumers articulated several technical issues within the mobile application, as indicated by the terms "login (login)", "upgrade (upgrade)", "update (update)", "versi (version)", "dibuka (opened)" and "buka (open)". Furthermore, several terms signify issues on the auction service's business operation, as evidenced by the words "uang (money)", "barang (item)", "jaminan (deposit)", and "daftar (register)".

Table 6. Top 15 Words in Negative Sentiment

Rank	Term/Word	Frequency
1	“lelang (auction)”	136
2	“aplikasi (application)”	129
3	“login (login)”	42
4	“upgrade (upgrade)”	38
5	“susah (difficult)”	35
6	“nya (its)”	35
7	“aplikasinya (the application”)	35
8	“uang (money)”	34
9	“barang (item)”	27
10	“masuk (enter)”	27
11	“jaminan (deposit)”	26
12	“buruk (bad)”	26
13	“update (update)”	25
14	“versi (version)”	24
15	“daftar (register)”	22

1) Word tree

To obtain a more comprehensive explanation of the patterns and interrelations of words and identify the main topics in a text, supplementary analysis utilizing a word-tree graph was performed. This graph enables the analysis of word meanings concerning their context, providing more detailed insights than the top word frequency phase. This study examined the word-tree graph of terms in both positive and negative sentiment reviews.

An instance of analysis of a word-tree graph for positive sentiment review text involves the root word "*mantap* (great)" which ranks as the second most appeared term in the positive sentiment category with 47 occurrences, as illustrated in figure 5. This word-tree graph, centered on the root word "*mantap* (great)" confirm several primary topics within the positive emotion category discovered during the top word frequency phase. For example, the first topic of high degree of customer satisfaction is illustrated by the branches of the term "*mantap* (great)" which include various positive terms such as "*bagus* (good)", "*sukses* (success)", "*keren* (cool)", "*ok* (ok)", and "*menang* (win)".

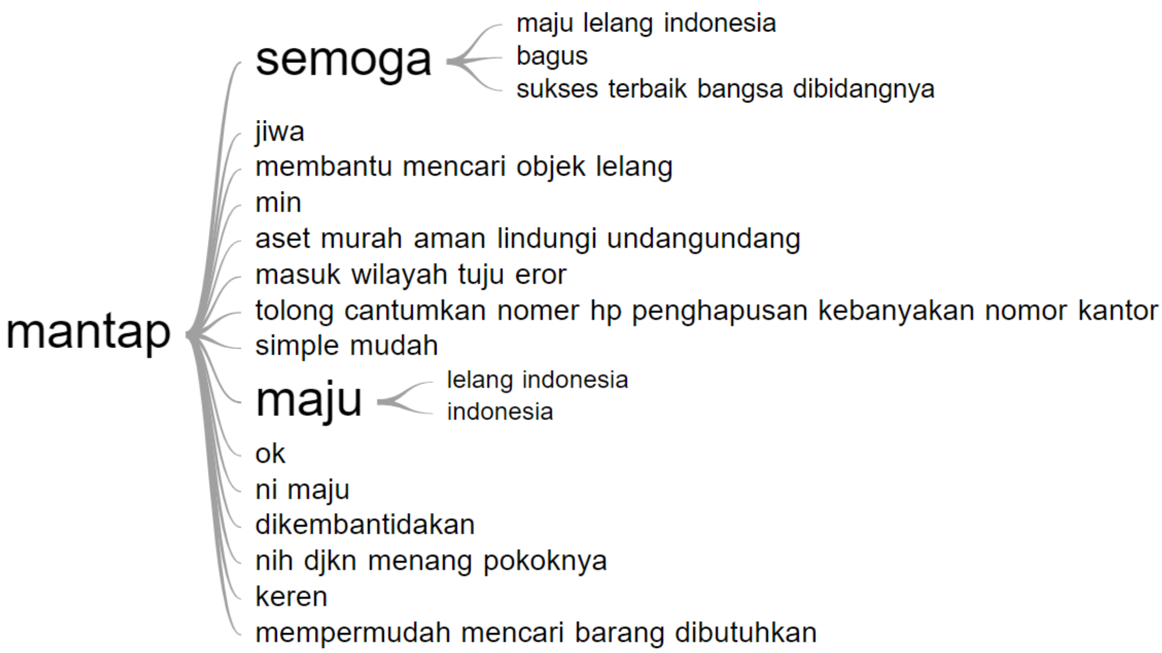

Figure 5. Positive Word Tree - "Mantap (Great)"

The second topic pertains to the ease of accessibility of auction services, as evidenced by the expressions "membantu mencari objek lelang (help find auction objects)", "simple mudah (simple easy)" and "mempermudah mencari barang diutuhkan (make it easier to find the items you need)". The third topic pertains to the hopes and aspirations expressed in the phrases "semoga maju lelang Indonesia (hopefully the Indonesian auction will progress)" and "semoga sukses terbaik bangsa di bidangnya (hopefully the nation's best success in its field)". Insights regarding new topics, namely concerning price and transaction security, were discerned from the word-tree graph, which were not effectively detected by top word frequency graph. This is exemplified by the phrase "aset murah aman lindungi undangundang (cheap assets are safe to protect the law)".

Conversely, the word-tree graph in figure 6 revealed that the root word "aplikasi (application)" is one of the most prevalent terms in the negative sentiment review text, ranking as the second most frequent word with 129 occurrences in this sentiment category. The word-tree graph rooted in "aplikasi (application)" corroborates several primary topics within the negative sentiment category found during the top word frequency phase. The first subject of low user satisfaction is showned by the derivatives of the term "aplikasi (application)" which include negative lexical words like "buruk (bad)". Furthermore, this word tree reveals a branch of terms that descibed additional negative words absent from the top word frequency phase, including "gila (crazy)", "kacau (chaotic)", "sampah (garbage)", "jelek (ugly)" and "parah (severe)".

Figure 6. Negative Word Tree "Aplikasi (Application)"

The word tree also reveals the second topic, which pertains to the challenges in acquiring auction services indicated by the word branch "*susah* (difficult)". The third topic pertains to technical issues associated with the branches "*update* (update)", "*lambat* (slow)", "*versi* (version)", "*buka* (open)", "*login* (login)", "*upgrade* (upgrade)", "*error* (error)" and "*dibuka* (opened)". The final topic pertains to the business process challenges of the auction service, as seen by the term branch which signifies requests for assistance and enhancement, articulated through the words "*mohon* (please)" and "*tolong* (help)".

1) N-gram Network

The last text mining phase conducted in this study is an n-gram network that shows the interactions among significant terms in user evaluations. This study employed a bigram network to illustrate the interaction between words, aiming to enhance contextual relevance while mitigating the danger of overfitting due to the constraints of the restricted dataset utilized. Bigram networks were analyzed for reviews encompassing both positive and negative sentiment categories.

The results of the top 30 bigram network for the positive sentiment category are illustrated in figure 7. Several terms serve as the focal point of the network, specifically the term "*mantap* (great)" which is linked to the core of another network, notably the terms "*aplikasi* (application)" and "*lelang* (auction)". This network suggests that certain users are satisfied and appreciate the existence of the Lelang Indonesia mobile application. Furthermore, people express optimism that the mobile application can offer support, convenience, and benefits to users, and it has the potential for further success in the future.

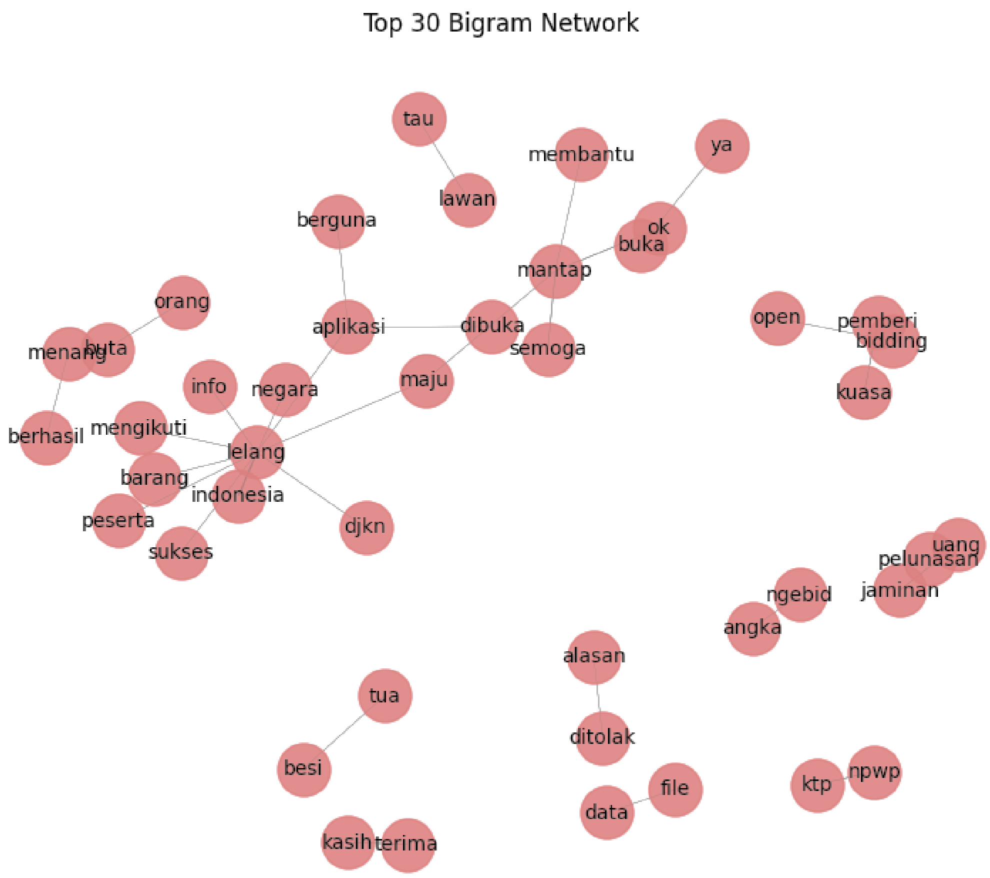

Figure 7. Top 30 Bigram Network for Positive Sentiment

Conversely, the findings from the top 30 bigram network for the negative sentiment category–illustrated in Figure 8–revealed several pivotal words, notably "lelang (auction)" which is interconnected with other central terms, specifically "aplikasi (application)" and "susah (difficult)". This network suggests that a significant number of users encounter difficulties utilizing the application due to technical issues related to the mobile application as indicated by the terms "web (web)", "versi (version)", "update (update)", "login (login)", "upgrade (upgrade)", "buka (open)", and "lemot (slow)" or challenges associated with the auction service's business processes as indicated by the terms "peserta (participant)", "jaminan (deposit)", "uang (money)", "pengembalian (refund)", "barang (item)", "mengikuti (participate)", "menang (win)", and "kalah (lose)".

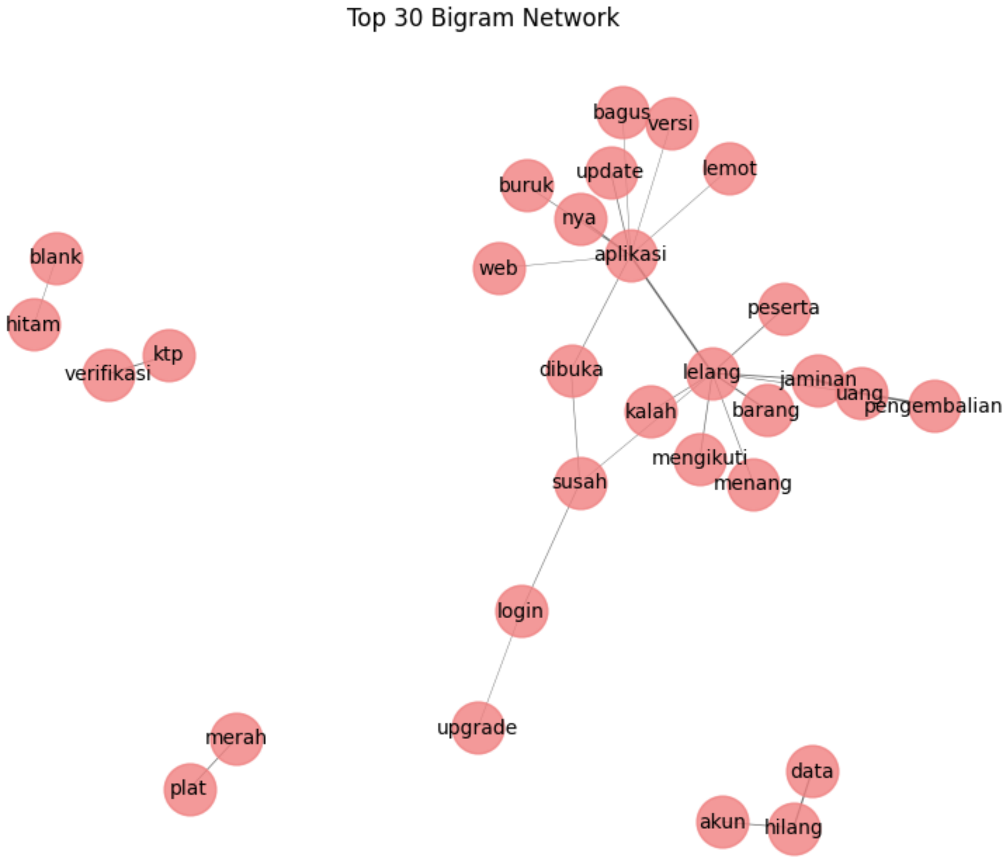

Figure 8. Top 30 Bigram Network for Negative Sentiment

Moreover, acknowledging that evaluations with unfavorable sentiments significantly impact the paradigm of the quality of public services, particularly for unconnected networks, remains a priority for organizations. This pertains to technological applications, namely the connections between the “blank (blank)” and “hitam (black)” networks, as well as the associations among the "hilang (missing)", "akun (account)", and "data (data)" networks. Additionally pertinent to the business process of auction services is the correlation between the "verifikasi (verification)" and "ktp (ID card)" networks.

Through sentiment analysis and text mining, this study identified significant insights that might assist institutions in assessing service quality and resources to enhance services in alignment with user expectations. This study found that positive sentiment reviews, characterized by satisfaction, praise, appreciation, and user expectations, can motivate institutions to deliver quality services while considering user feedback.

Institutions must devote special attention to reviews categorized as negative sentiment and implement thorough service enhancements, as such reviews adversely affect the reputation of these public institutions and public services in Indonesia. This study revealed insights into issues arising from both the technical aspects of the application, shown in table 7, and the business processes of auction services, shown in table 8, along with recommendations to address and resolve these issues.

Table 7. Technical Issues/Problems with The Application

No.	Issues	Recommendations
1.	Issues related to update	Institutions must test application updates before public release and ensure no errors occur.
2.	Issues or problems related to application login/access/entry	Provide clear error messages, password recovery options, log monitoring, and good user support service.
3.	Issues related to slow-running application	Perform application performance analysis, code and graphics (UI/UX) optimization, and server performance improvement.
4.	Issues related to filter or search	Use appropriate search and data filter algorithms.
5.	Issues related to interface that is not user-friendly	Develop UI/UX according to user preferences and conduct direct testing with people.
6.	Maintenance-related Issues	Carry out careful maintenance planning and continuous development of mobile applications.
7.	Issues related to account/data loss	Mitigate risks by implementing data backup and encryption and enhancing data security protocols.

Table 8. Issues/Problems in Business Process

No.	Issues	Recommendations
1.	Issues related to registration and identity verification (KTP/NPWP) of users	If an institution conducts manual document verification, ensure it has a dedicated and responsive team of verifiers.
2.	Issues related to refund of the auction deposit money	Automate the refund of auction deposits, issue notifications to users, and deliver efficient and timely user support.
3.	Issues related to insufficient information	Establish regulations and standardize the information required to be sent to users within the application while ensuring effective and responsive user services.

Conclusion

This study aims to assess user satisfaction with the Lelang Indonesia mobile app by detecting and assessing user perceptions and sentiments as expressed in their reviews on the Google Play Store. Additionaly, this study seeks to identify and analyze the primary underlying themes or topics associated with users' reviews of the auction service.

This study introduced a sentiment analysis model employing machine learning to understand user opinions regarding the Lelang Indonesia mobile application service. The data analysis used opinions derived from 656 user reviews extracted from the ratings and reviews section of the Google Play Store. The generated sentiment analysis model shows an accuracy rate of 85% and an F1-Score of 84%. The study revealed that 55% of Lelang Indonesia mobile application users expressed unfavorable views, while 45% expressed positive sentiments regarding the application. Consequently, the sentiment analysis indicates that the number of users of the Lelang Indonesia mobile application who experience dissatisfaction exceeds those who experience satisfaction.

The primary topics within the positive sentiment category expressed by users encompass the assistance rendered in the auction service, expressions of gratitude or appreciation from users towards the auction service, and users' aspirations and expectations for the better auction service in the future. On the contrary, the significant number of users expressed negative feelings, highlighting two primary concerns: issues related to the technical application and issues related to the business processes of auction services. This study presents multiple recommendations for the institution to address concerns and improve auction services in alignment with customer expectations and aspirations.

This study offered an alternative to mobile-based public service satisfaction evaluation methods, addressing the present limitation in public service evaluation, specifically the lack of real-time assessment methods. By employing sentiment analysis and text mining, particularly concerning service user reviews, institutions can swiftly, effectively, and accurately acquire insights, thereby establishing an novel method for assessing public service satisfaction. This method aids in identifying primary topics that emerge as issues for users, enabling institutions to proactively address these concerns and serve as a foundation for enhancing public services, particularly mobile application-based services, in alignment with user expectations.

This study has various limitations, namely the restricted dataset, as it solely utilizes review data from the Google Play Store. The second constraint pertains to sentiment analysis reliant on manual annotations derived from rating scores, which may result in discrepancies between the rating scores and the reviews provided by users. Consequently, this constraint might be addressed in future research by expanding the sources of review datasets, particularly by incorporating datasets from other platforms, such as social media reviews. Furthermore, the study can be enhanced by implementing sentiment analysis via a lexicon-based approach, allowing for a comparative evaluation of the model's performance.

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