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MEASURING CUSTOMER SATISFACTION OF AN E-COMMERCE COMPANY BASED ON OPINION MINING USING SVM ALGORITHM, CSI AND IPA

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Original Scientific Paper

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This study was carried out to examine the perceived service quality of an e-commerce company app users and the measures that may be taken to improve customer satisfaction. The analysis techniques used were opinion mining to analyse reviews on the Google Play Store, e-SERVQUAL and Customer Satisfaction Index (CSI) to assess customer satisfaction, and Importance-Performance Analysis (IPA) to identify elements that require improvement. According to the findings of opinion mining, 65.86% of e-commerce company application users were satisfied, while 34.14% were dissatisfied. Customer satisfaction levels were classified as satisfied for the dimensions of efficiency and reliability, and fairly satisfied for the dimensions of fulfilment, compensation, and responsiveness, based on questionnaire distribution. The Importance Performance Analysis method was used to determine the priority for service quality improvement. Findings showed that delivery time, product suitability, refund and return policy, and service time were the top priorities for service improvement.

Keywords: Customer Satisfaction Index; E-Servqual; E-commerce; Importance Performance Analysis; Opinion Mining; Support Vector Machine.

INTRODUCTION

E-commerce is defined as a platform for buying and selling activities that use electronic technology to connect companies, producers, consumers, and the general public in electronic transactions (Chong & Ali, 2022). According to data from the We Are Social survey conducted in April 2021, 88.1% of internet users in Indonesia used e-commerce to shop online (OJK, 2022). This indicates that many Indonesians conduct buying and selling transactions through online media. This means that e-commerce has become a viable business option in the modern era, resulting in increasingly competitive competition in line with current market conditions.

Customers typically provide feedback on the company's services via online media, one of which is the Google Play store in order to improve the quality of its service, the company should review customer comments on the app. This is critical because comments on the Play Store can have an impact on the company's image for both new and returning customers. As a result, all complaints about the e-commerce application posted in the Google Play store comment section must be read and addressed. However, because there are so many comments, the management process cannot be done manually One method for analysing comments on the Google Play store is to use opinion mining or sentiment analysis (Yanuargi, 2022).

Opinion mining is a method that focuses on extracting dominant subjects from given texts or analysing subjectivity (Gupellil & Boukhalfa, 2015). In this process, the analysis uses algorithms such as Nave Bayes, Support Vector Machine, K Nearest Neighbour, Association, and others (Al-Shufi & Erfina, 2021) to process user reviews of products and services that contain large amounts of

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unstructured text (Brahimi et al., 2019). According to several references, the Support Vector Machine produces the highest accuracy in sentiment analysis when compared to other classification algorithms (Hendriyanto et al., 2022).

The key characteristics of opinion mining are, first and foremost, the modelling of opinions, which focuses on how opinions are formalised. Second, opinion extraction involves generic or multiple issues, as well as statements that include opinions or opinion holders. Finally, subjectivity analysis is when an opinion is regarded as objective if it comprises facts, and subjective if it represents an opinion (Gupellil & Boukhalfa, 2015).

Opinion mining data sources include blogs, review sites, and micro-blogging platforms such as Twitter, Tumblr, and Facebook (Buche et al., 2013) whose purpose is to understand customers' opinions toward a product (Hapsari et al., 2018), including whether they have negative or positive opinions (Rozi et al., 2012). It can also be used in business to understand how customers react to a marketed product (Sitorus, 2022). Customers' texts or reviews, on the other hand, are generally subjective. The polarity of the sentiment is determined as negative or positive in binary categorization, which assumes that the text is mostly negative or positive. Negativity and positivity may be associated with dissatisfaction and satisfaction in the context of tourism (Andrian et al., 2022).

Sentiment analysis can interpret the good or bad of products or services based on the users' perspectives and feelings. According to Rhajendra and Trianasari (2021), Google Play reviews can provide insight into consumer needs and desires for developing services and improving customer satisfaction. Sasmita et al. (2021) found that sentiment analysis is necessary to maintain service quality and create customer loyalty. Sentiment analysis, on the other hand, cannot provide detailed suggestions for improvement because it only provides attributes that influence consumer sentiment in related applications (Ginting, 2021).

Customer satisfaction is the level of satisfaction that a customer feels when the performance of a company's products or services meets their expectations. A company's good service to its customers becomes a consideration because it serves as a benchmark for measuring customer satisfaction levels for a service or product (Firdiana, 2018).

Research conducted by Sihite (2021), used the Customer Satisfaction Index (CSI) and Importance Performance Analysis (IPA) methods. CSI can indicate the dimensions of service quality that need improvement, while IPA will show how important those attributes are according to users. Another research used IPA to map the overall indicators of service quality dimensions to find priority areas for improvement (Deo et al., 2017).

According to previous research, opinion mining can be used to analyse e-commerce to service quality based on Google Play Store reviews, followed by the use of CSI to evaluate customer satisfaction with the service provided based on e-Servqual dimensions, and IPA identifies areas that require improvement. This allows service providers to identify areas for improvement and provide feedback to the company in order to maximize customer satisfaction with the services provided. Further in this paper authors use Y to represent an e-commerce company used in this study.

According to a recent survey, *Y* application is an e-commerce platform that sells various types of daily necessities and has fluctuating value as a Top Brand Award. This fluctuating value indicates that Y has not been able to satisfy customers. There is still a gap between the service customers receive and their expectations. As a result, there is a need to further investigate this topic using available literature, data, and tools, both theoretically and practically. The following are the research questions:

1. What are the e-commerce *Y* application users' views based on opinion mining?
2. What is the level of customer satisfaction with *Y* application services?
3. What are the most important service enhancements that can be made to the *Y* application?

METHODOLOGY

The study's population consists of all people who have used *Y* Application services in Makassar City. Purposive sampling was used in this study, which means that sample members were chosen to serve as information sources based on their experience and ability to provide information/ data to answer research questions (Ginting, 2021). This study's data collection steps are divided into two stages. The first step is to scrape customer reviews from the *Y* app on the Google Play Store for further sentiment analysis. The Python programming language is used to scrape the *Y* review data from the Google Play Store website. A total of 50.000 recent reviews were collected between August 2021 and November 2022. The second stage entails distributing a Google Forms-based customer satisfaction evaluation questionnaire with sub-attributes based on the most frequently occurring words in customer sentiments. The questionnaire includes questions with two Likert scale answers: the level of importance and the level of performance. There are 16 questions spread across five service quality dimensions: efficiency (3 questions), fulfilment (4 questions), compensation (3 questions), reliability (3 questions), and responsiveness (3 questions). After gathering the data, the next step is to analyse it. Data analysis includes sentiment analysis of *Y* user reviews as well as customer satisfaction measurement via gap analysis and the customer satisfaction index. IPA is also used to identify priority attributes for improvement, which can provide valuable insights to the relevant company.

The data collected during the scraping process is not always in a suitable state for processing. Missing values, redundant information, outliers, or data formats that do not align with the system can all occur in data.

Data preprocessing involves several stages, including those mentioned by Putri et al. (2022): 1) Cleansing involves eliminating from the data attributes that are irrelevant to the information present, such as URLs, hashtags (#), usernames (@username), emails, emoticons (:@,:*,:D), punctuation marks such as commas (,), periods (.), and other punctuation; 2) Case folding standardizes the letter case in the data, making all characters lowercase; 3) Tokenizing is the process of breaking down a sentence into words or separating text data into multiple tokens; 4) Normalization is the process of converting non-standard or misspelled words into standard words by using a dictionary database of standard and non-standard words generated from the comment data; 5) Filtering is the process of removing unnecessary words such as conjunctions, prepositions, exclamatory words, pronouns, and adverbs without affecting the overall data from the tokenizing process; 6) Stemming is the stage in which words with prefixes are converted or each word from the previous filtering process is returned to its base form.

After cleaning the data, it was divided into training and test sets. The training data is used to train the model, while the test data is used to evaluate the model's performance in predicting previously unseen data (Aripin et al., 2021). Data splitting ratios that are commonly used include 60:40, 70:30, and 80:20. A 60:40 data split, for example, means that each dataset will be divided into 60% for training data and 40% for test data. This is also true for other data-splitting ratios (Irianandaet al., 2021).

The support vector machine algorithm is used to perform sentiment classification after the data has been divided. SVM's goal is to find the best line between the two classes. This line is known as a hyperplane in higher dimensions, which is a line or, more technically, a discriminant that separates two classes in an n-dimensional space (Bisong, 2019). When the model predicts the target from previously unseen examples, its performance on the training data is evaluated to obtain the accuracy of the training set, while its performance on the test data is evaluated to obtain the accuracy of the test data.

The results of opinion mining are then visualized in the form of a word cloud, which displays the frequency of the most frequently occurring words. Words that appear frequently will be used to create a questionnaire, which will be distributed to analyse customer satisfaction levels.

The questionnaire includes questions with two Likert scale answers: the level of importance and the level of performance There are 16 questions spread across five service quality dimensions: efficiency (3 questions), fulfilment (4 questions), compensation (3 questions), reliability (3 questions), and responsiveness (3 questions). After gathering the data, the next step is to analyse Data analysis including sentiment analysis of f-user reviews as well as customer satisfaction measurement via gap analysis and customer satisfaction.

RESULT AND DISCUSSION

Opinion Mining

The first step in this research is to conduct opinion mining or sentiment analysis. The data used was obtained by scraping Google Play store results. The information gathered is based on the most recent review from Y app users. Figure 1 shows the number of reviews for each rating based on the star rating.

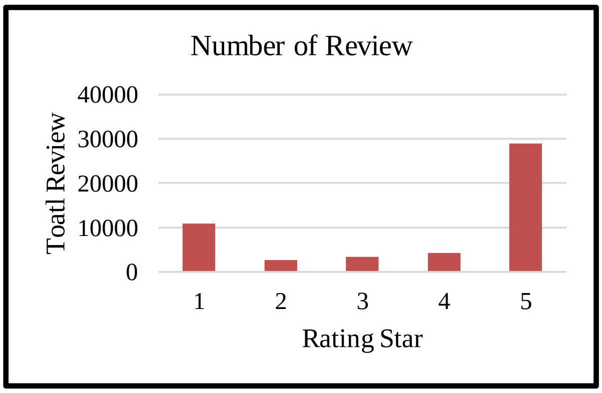

Figure 1: Classification Results

According to Figure 1, 28,847 users gave a 5-star rating in their review, 4,208 reviews received a 4-star rating, 3,359 reviews received a 3-star rating, 2,682 reviews received a 2-star rating, and 10,904 reviews received a 1-star rating. The data was then marked with a label-1 for positive reviews or ratings of 5 or 4 stars. Meanwhile, label -1 was assigned to negative reviews or those with three, two, or one stars. According to the labelling results, 33,055 reviews were labelled as positive and 16,945 as negative.

Subsequently, labelled data will go through the preprocessing stage. The preprocess data follows these stages:

1. Case folding is the process of converting the letter case in data to lowercase.
2. Data cleansing is the process of removing attributes from data that are unrelated to the information in the data.
3. Tokenization, which is the process of dividing text data into tokens.
4. Normalization is the process of transforming non-standard words into standard words.
5. Stop word removal is the process of removing unnecessary words.
6. Stemming is the process of converting affixed words into their basic form.

The sample data is then divided into two categories: train data and test data, with 75% and 25%, respectively. The support vector machine algorithm is then used to perform sentiment classification, yielding a maximum accuracy value of 86.61%. It is possible to conclude that the system developed is effective at representing customer sentiment. Figure 2 depicts a recapitulation of sentiment analysis results from 25% of the dataset.

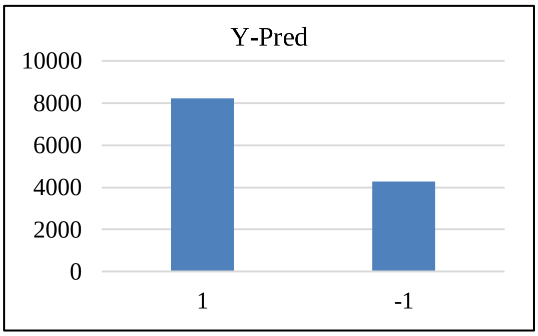

Figure 2: Classification Results

According to Figure 2, out of 12,500 reviews used as testing data in the research sample, 8,233 (65.86%) *Y* application users gave positive sentiment reviews, while 4,267 (34.14%) users gave negative sentiment reviews. In other words, 34.14% of *Y* application users in the research sample who were used as testing data were dissatisfied with the service they received.

The final step is to test the level of accuracy. The classification accuracy using the support vector machine algorithm is 86.61%. As a result, the accuracy level of the support vector machine algorithm is greater than 80%, implying that it is effective in opinion mining regarding *Y* application review data. A classification report containing a confusion matrix, precision, recall, and f-1 score will be generated from the previously built model. Figure 3 depicts the classification results obtained with the system built using the support vector machine algorithm.

Following that, the most frequently used words in customer sentiment are displayed. The most frequently used words will be used to develop a questionnaire that will be distributed to assess customer satisfaction.

```
Accurasy of SVM Classifier on test set 0.866080
[[3456  863]
 [ 811 7370]]
              precision    recall  f1-score   support

          -1       0.81      0.80      0.81      4319
           1       0.90      0.90      0.90      8181

    accuracy                           0.87     12500
   macro avg       0.85      0.85      0.85     12500
weighted avg       0.87      0.87      0.87     12500
```

Figure 3: Result of Confusion matrix

Several words that influence negative customer sentiment, including *Y*, application, order, product, disappointed, delivery, payment, store, and please. The more words in customer reviews that appear, the more influential they are in shaping customer sentiment. As a result, special consideration must be given to related factors in order to meet customer expectations. These words will serve as the foundation for developing sub-attributes for the customer satisfaction questionnaire. The questionnaire distribution will be more effective and focused on discussing the words that influence customer opinions, allowing the company to specifically identify what improvements should be made to meet customer expectations.

Customer Satisfaction Measurement

The questionnaire is divided into two sections: demographics and questions about quality of service. Customer satisfaction was measured using a five-point Likert scale. The demographics of the respondents are shown in Table 1.

Table 1: Respondent characteristics

Demographics	Item	Frequency	Percentage
Gender	Male	31	22%
	Female	112	78%
Age	Less than 20	29	20%
	21-25	107	75%
	26-30	7	5%
Job	Student	118	83%
	Employees	13	9%
	Housewives	5	3%
	Entrepreneurs	4	3%
	Freelancers	2	1%
	Civil Servants	1	1%
Length of application uses	Less than 1 year	69	48%
	1-2 year	26	34%
	More than 2 years	48	18%

Validity and Reliability Test

The validity test is used to determine whether the statements in the questionnaire that have been created to become research instruments are valid. If the calculated r-value is greater than the table r-value, the data is considered valid. The reliability test determines the level of consistency of a measuring tool used in the research, allowing it to determine whether or not the questionnaire is reliable. If Cronbach's alpha coefficient value is greater than 0.6, a questionnaire is considered reliable or consistent. If the Cronbach's alpha value is less than 0.6, the questionnaire is considered untrustworthy/ inconsistent. Table 2 shows the results of the validity test on the performance assessment of the *Y* application.

The table above shows that all questions have a calculated r-value greater than the table r-value, indicating that all indicators are valid. Table 3 displays the findings of the reliability test indicating that all dimensions have Cronbach's alpha values greater than 0.6.

Gap Analysis

To determine which indicators, fall short of user expectations, a gap analysis is employed. Table 4 presents an overview of the gap analysis for *Y*'s services.

Table 2: Validity Test

No	Dimension	r-table	r-value of Performance	r-value of Expectation	Description
1	Efficiency	0.164	0.596	0.624	Valid
		0.164	0.692	0.684	Valid
		0.164	0.729	0.700	Valid
2	Fulfilment	0.164	0.783	0.855	Valid
		0.164	0.761	0.851	Valid
		0.164	0.792	0.706	Valid
		0.164	0.764	0.687	Valid
3	Compensation	0.164	0.835	0.870	Valid
		0.164	0.836	0.857	Valid
		0.164	0.771	0.864	Valid
4	Reliability	0.164	0.680	0.731	Valid
		0.164	0.769	0.863	Valid
		0.164	0.773	0.882	Valid
5	Responsiveness	0.164	0.825	0.838	Valid
		0.164	0.745	0.864	Valid
		0.164	0.834	0.901	Valid

Table 3: Reliability Test

Dimension	Cronbach's Alpha of performance level	Cronbach's Alpha of expectation level
Efficiency	0.842	0.868
Fulfilment	0.897	0.864
Compensation	0.925	0.969
Reliability	0.873	0.894
Responsiveness	0.933	0.966

Table 4: Gap Analysis Result

Dimension	Indicator	Performance	Expectation	Gap
Efficiency	P1	3.664	3.909	-0.245
	P2	3.531	3.888	-0.357
	P3	3.392	3.937	-0.545
Fulfilment	P4	3.084	4.336	-1.252
	P5	3.098	4.476	-1.378
	P6	3.189	3.860	-0.671
	P7	3.105	3.629	-0.524
Compensation	P8	3.105	4.427	-1.322
	P9	3.077	4.441	-1.364
	P10	3.224	4.308	-1.084
Reliability	P11	3.531	3.993	-0.462
	P12	3.357	4.182	-0.825
	P13	3.329	4.259	-0.930
Responsiveness	P14	3.196	4.287	-1.091
	P15	3.266	4.252	-0.986
	P16	3.294	4.308	-1.014
Total		**3.278**	**4.156**	**-0.878**

It is evident from the above table that all indicators in each service dimension result in negative gaps, with an average gap value of -0.878. This means that overall, the perceived performance does not meet the expectations of the application users. The largest gap value between performance and expectations is found in the fulfilment dimension, specifically in indicator P5. The obtained gap value of -0.1378 suggests that users think the items they ordered and the ones they received are not always the same.

Customer Satisfaction Index

Table 5 presents the results of the customer satisfaction index for all dimensions.

Table 5: CSI Calculation Results

Dimension	CSI Value (%)	Description
Efficiency	70.576	Satisfied
Fulfilment	62.345	Fairly satisfied
Compensation	62.687	Fairly satisfied
Reliability	68.064	Satisfied
Responsiveness	65.036	Fairly satisfied

The results of the CSI analysis for *Y*are are in line with the gap analysis calculation, where the dimension that requires improvement is the fulfilment dimension, which has the largest gap between performance and expectation. Using the CSI method, the fulfilment dimension is classified as "Fairly Satisfied."

Importance-Performance Analysis

Importance Performance Analysis (IPA) is used to determine the priority of improvements based on the level of performance and expectation of the service provided. The questionnaire indicators are then mapped into a Cartesian diagram from the most important to the least important. This can be used to further plan the priority of improvements to meet customer expectations. The importance of the performance analysis of *Y*'s services for each research indicator can be seen in Figure 4.

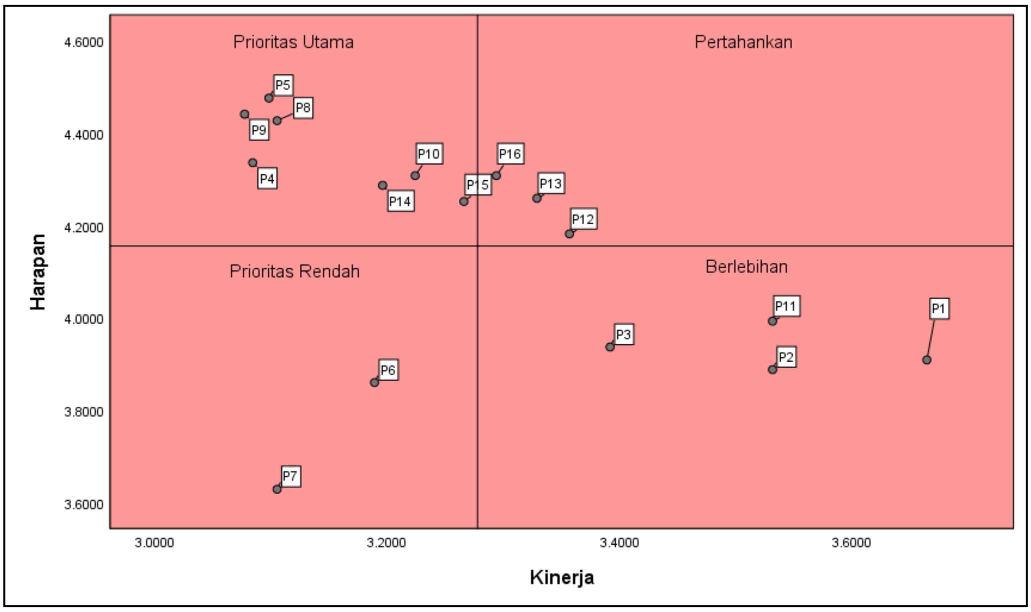

Figure 4: Results of Applying IPA to Y Application

Based on the figure above, seven indicators fall into Quadrant I (High Importance, Low Performance), which are the priority areas for improvement for *Y*'s services, as shown in Table 7.

The recommendations for service improvement are as follows:

1. P4 → the *Y* platform to increase the accuracy of delivery time predictions and provide contact information for the delivery service provider to the customers.
2. P5 → to verify the products with the seller before sending them to the customer to ensure that they match the order and description.
3. P8 → the refund process will be carried out in real-time, eliminating the need to contact the call centre for clarification.
4. P9 → to provide free shipping for returns subject to terms and conditions.
5. P10 → the refund process for shipped transactions to be processed and returned in real-time with no additional confirmation.
6. P14 → to arrange the pickup of returned products in order to give a positive impression of the return process, while keeping the

transaction amount to a minimum in order to avoid significant losses.

7. P15 → to conduct periodic employee reviews to ensure that they are dependable and capable of providing prompt service to customers.

Table 7: Quadrant I

Indicator	Statement
P4	The goods are delivered according to the estimated time.
P5	The items received and those ordered are the same.
P8	Refunds are given when the goods received are incorrect or damaged.
P9	When the goods received are incorrect or damaged, they are returned.
P10	Order cancellations (automated cancellation/store/customer) are refunded.
P14	*Y* handles the return of goods very well.
P15	*Y* responds quickly to existing issues.

Indicators in Quadrant II (High Importance, High Performance) contain indicators with good performance that must be maintained. Table 8 displays the Quadrant II indicators for *Y*'s services.

Table 8: Quadrant II

Indicator	Statement
P12	Clear information was provided regarding the shipment of goods.
P13	The application's description of the goods matches reality.
P16	*Y* offers guarantees as mentioned.

Indicators in Quadrant III (Low Importance, Low Performance) have low-performance levels and low customer expectations. As a result, they are designated as low priority and less important for improvement. Table 9 shows the Quadrant III indicators for *Y*'s services.

Table 9: Quadrant III

Indicator	Statement
P6	The offered promotions are applicable at the time of payment.
P7	Free shipping is provided with a minimum purchase.

Indicators located in Quadrant IV (Low Importance, High Performance) contain indicators that are not too important but have good performance levels. Therefore, no further action is needed for indicators located in this quadrant. The Quadrant IV indicators for *Y*'s services can be seen in Table 10.

Table 10: Quadrant IV

Indicator	Statement
P1	The provided promotions are valid at the time of payment.
P2	Payments are made more easily.
P3	Easy account creation on the *Y* app.
P11	Transactions are made easier because a variety of payment methods are available.

CONCLUSIONS

Users of the *Y* app leave reviews on Google Play, which are classified as either positive or negative. According to the results of opinion mining using the Support Vector Machine algorithm, which has an accuracy rating of 86.61%, there are 65.86% positive sentiment reviews and 34.14% negative sentiment reviews. The sentiment analysis output serves as the foundation for determining service quality characteristics. Efficiency, fulfilment, compensation, reliability, and responsiveness were chosen as service quality dimensions.

The CSI analysis results for *Y* are consistent with the gap analysis calculation, with the fulfilment dimension requiring the most improvement due to the largest gap between performance and expectation. According to the CSI method, the fulfilment dimension is "Fairly Satisfied.". According to the findings, the top priorities for improvement are delivery time, product accuracy, refund and return processes, and service speed.

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MERENJE ZADOVOLJSTVA KORISNIKA KOMPANIJE ZA E-TRGOVINU ZASNOVANO NA POSTUPKU *OPINION MINING*-A POMOĆU SVM ALGORITMA, CSI I IPA

Ova studija je sprovedena da bi se ispitao percipirani kvalitet usluge korisnika aplikacije kompanije za e-trgovinu i mere koje se mogu preduzeti da bi se poboljšalo zadovoljstvo korisnika. Korišćene tehnike analize bile su: prikupljanje mišljenja za analizu recenzija u *Google Play* prodavnici, e-SERVKUAL i Indeks zadovoljstva korisnika (*Customer Satisfaction Index* - CSI) za procenu zadovoljstva kupaca i Analiza važnosti performanse (*Importance-Performance Analysis* - IPA) kako bi se identifikovali elementi koji zahtevaju poboljšanje. Prema nalazima istraživanja mišljenja, 65,86% korisnika aplikacija kompanije za e-trgovinu bilo je zadovoljno, dok je 34,14% nezadovoljno. Nivoi zadovoljstva kupaca su klasifikovani na osnovu distribucije upitnika kao: zadovoljni za dimenzije efikasnosti i pouzdanosti, i prilično zadovoljni za dimenzije ispunjenosti, kompenzacije i odziva. Za određivanje prioriteta za poboljšanje kvaliteta usluge korišćen je metod IPA. Nalazi su pokazali da su vreme isporuke, prikladnost proizvoda, politika refundiranja i vraćanja, kao i vreme usluge bili glavni prioriteti za poboljšanje usluge.

Ključne reči: Indeks zadovoljstva korisnika; e- Serkval; e-Trgovina; Analiza važnosti i performanse; Opinion Mining; Mašina sa vektorima podrške.