Kontigensi: Jurnal Ilmiah Manajemen
Vol 11 , No. 2 December 2023, pp. 513-527
ISSN 2088-4877

Analysis of Service Science Design through Customer Experience to Increase PosAja Application User Satisfaction

[1]Sukma Rukmana, [2]Wiwik Handayani
[1,2]Management Study Program, Faculty of Economics and Business, Universitas Pembangunan Nasional "Veteran" Jawa Timur, Surabaya, Indonesia
E-mail: 19012010050@student.upnjatim.ac.id[1], wiwik.em@upnjatim.ac.id[2]

DOI: https://doi.org/10.56457/jimk.v11i2.402

Received: August 2023	Accepted: November 2023	Published: December 2023

ABSTRACT

The PosAja mobile application is a digital service owned by Pos Indonesia in the field of delivery. Despite being downloaded by more than 100K users, the PosAja application has experienced a decline in rating and application productivity. This research intends to represent user complaints through review data analysis and develop a more effective and efficient service science design based on user experience. The research method applied is descriptive quantitative with data analysis applying SVM to classify positive and negative sentiments from review data. Model evaluation was carried out by training the training and test data subsets 3 times with variations of k = 5, k = 7, and k = 10. The results showed that the best accuracy was obtained with an accuracy of 89.98% on the SVM_kernel Sigmoid parameter. Analysis of review data revealed that the sentiment of PosAja application users tends to be negative compared to positive sentiment on the Google Play Store. To improve user experience and satisfaction, service science design development should focus on continuous improvement and evaluation of the PosAja application.

Keywords: Customer Experience; Operations Management; Service Science; SVM; User Satisfaction

INTRODUCTION

Today, the service sector plays a crucial role in the global economy. Competition is intensifying in this sector due to advancements in the industrial revolution and information technology. In industrial revolution 5.0, the focus is given to the integration between digital and physical technologies in a system that involves human collaboration as an essential partner to achieve a more adaptive, intelligent, and sustainable industrial transformation.

Joint value creation or collaboration involves the interaction and development of stakeholders through platforms. As information technology has evolved, these platforms have transformed into electronic platforms such as mobile applications and websites that facilitate interaction between consumers and service providers. Electronic services use Information Technology (IT) to provide effective systems, change, or realize evaluations on current and potential consumers (Revika & Handayani, 2022). E-Service Quality refers to the level of convenience offered by websites that enable the process of shopping, purchasing, and delivering goods and services efficiently and effectively (Permana & Djatmiko, 2018). Electronic service quality involves customer interaction with online services and consists of two main components, namely technical quality and functional quality. According to (Prasuraman et al in Hizam & Ahmed, 2019), four main dimensions cover electronic service quality, namely efficiency, fulfillment of needs, system availability, and privacy. Efficiency relates to the ease and speed of access and use of the site, fulfillment of needs includes the accuracy of company performance, system availability relates to the functionality and usability of the site, and privacy involves the protection of user information.

The rapid advancement of information technology also has an impact on competition among similar e-service products. Therefore, for e-services to be able to persevere and compete

in today's competitive era, businesses must continue to innovate in service systems and improve service quality to meet user needs. Innovation in service systems requires the integration of multidisciplinary knowledge to adapt and consider how the interaction of people, technology, organizations, and information creates value in various contexts and conditions (Maglio, et al., 2019). Service science incorporates this understanding to categorize and explain different types of service systems and how they interact and evolve to create value. Service science covers a wide range of aspects, from automated interactions between computers to personalized services that involve direct interactions between individuals (Luigi Cantone, 2019). It also covers a wide range of service activities, whether local or large service systems such as governments, as well as industry classifications of companies such as service, industry, or agriculture.

The essence of service science is to always focus and prioritize customer experience (CX) over time (Bolton, 2019). CX has a central role in the success of e-services, as it has a direct link to user satisfaction. Customer Experience (CX) refers to the customer's overall perception of the physical and emotional experience of using the company's products, systems, and services. This customer experience is subjective and can affect the value of products and interactions with the company (Bascur & Rusu, 2020). Customer experience involves various interactions, such as website visits, transactions, app navigation, customer service, and product receipt. Companies need to understand these various interactions as user experiences, both positive and negative, and respond quickly to customer complaints so that the customer experience is not negatively affected. Within the framework of Customer Relationship Management (CRM), customer information is used to manage long-term relationships and customer value. However, companies usually have more quantitative CRM data related to customers' purchasing habits and classifications, while information about customers' emotions and their judgment is still less known (Sartika, et al., 2023).

Big Data Analytics (BDA) is used to gain an understanding of the customer journey and support decision-making that can improve the customer experience (Holmlund, et al., 2020). Through text mining techniques and machine learning natural language processing, text data analysis can help analyze customer emotions and evaluations in sentiment analysis (Hasibuan & Heriyanto, 2022). This approach enables the extraction of insights from customer survey data covering customer activities and resources, company activities and resources, and customer sentiments such as compliments and complaints. Using text mining, customer data is not only categorized as positive or negative but also associated with activities and resources that explain how value is created through the voice of the customer. Companies globally are increasingly focusing on CX and many plans to improve their CX programs by expanding the use of predictive analytics, artificial intelligence (AI), and journey analytics (Dorsey, Temkin, & Quaadgras, 2022). According to Indonesian Consumers' Areas for CX Improvements 2022, the industry that excels most in customer experience in Indonesia is the online resources industry. Online resources include data, documents, and software that can be accessed through the Internet and the World Wide Web (www). CX and AI work together to improve user satisfaction through optimized and efficient service by utilizing in-depth data analysis and AI's ability to understand and respond to users' needs and emotions.

Artificial Intelligence (AI) itself is a discipline that refers to the field of computer science that focuses on creating software and hardware that can mimic some of the functions of the human brain. AI involves teaching computers to learn, think, communicate, and make decisions like humans (Tresnawati, Guno, Satwika, Prihatmanto, & Mahayana, 2022). In processing information, AI uses symbols and heuristic methods, but AI cannot replace the role of humans entirely. Instead, AI serves as a support for the performance of Human Resources (HR). Therefore, it is important to develop HR competencies that AI cannot do, such as improving soft skills. In the context of AI, there are

four known types of intelligence, namely mechanical intelligence, analytical intelligence, intuitive intelligence, and empathetic intelligence (Zein, 2021). In addition, AI also involves evolving technologies, such as natural language processing (NLP), which is used to understand and utilize natural language in sentiment analysis and text mining (Putro, et al., 2023).

It is predicted that Indonesia will be the ASEAN leader in AI adoption due to its large population, high penetration of mobile phone users, and significant growth in internet usage (Asosiasi Penyelenggara Jasa Internet Indonesia (APJII) , 2022). Some sectors that are aggressively adopting AI in Indonesia include banking, government, manufacturing, and retail (Venkatesh, et al., 2022). Examples of common AI uses include fraud analysis, business innovation and automation, product suggestion, general security, and virtual customer service (conversational AI). The Indonesian government plans to use AI in public service reforms to improve efficiency, fairer access, and a better service experience. Although Indonesia still lags in public service digitization and AI adoption compared to other countries, the country has made significant progress. Indonesia is ranked 43rd globally in the AI index and 9th in the Asia Pacific (Rogerson, Hankins, Nettel, & Rahim, 2022).

One of the government companies applying AI in business innovation and service automation is Pos Indonesia, the largest and oldest logistics service company in Indonesia. Despite being the largest and oldest, Pos Indonesia faces competition from similar companies such as JNE, J&T, Tiki, SiCepat, DHL, FedEx, and Armex. The top brand index surveys over the past five years reflect competition in the courier services category and subcategory, as shown in the following graph:

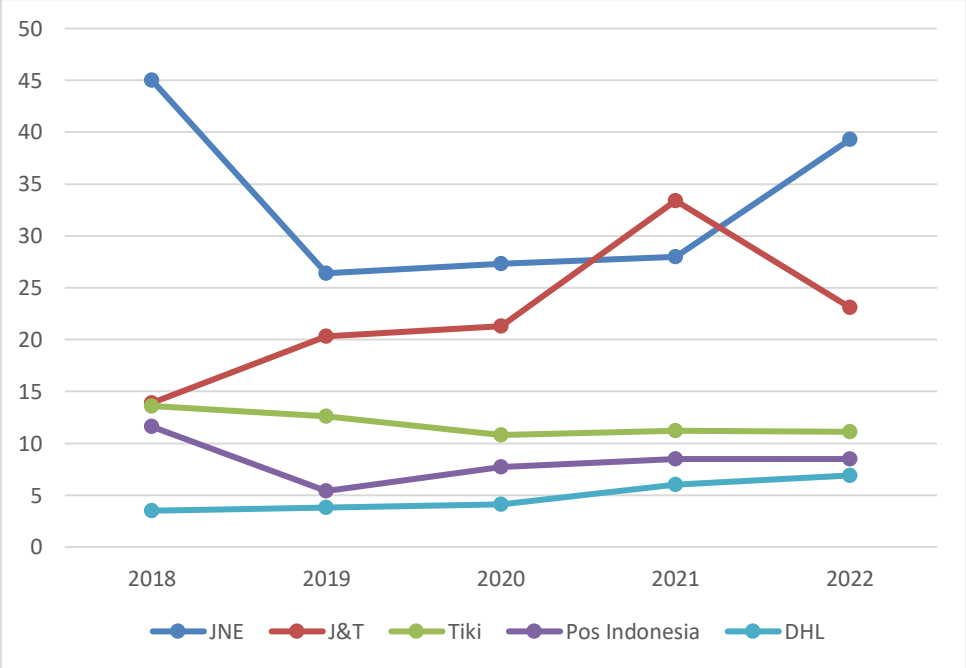

Figure 1. Top Brand Index 2022
Source: Top Brand Index (2022)

Pos Indonesia experienced a significant gap compared to J&T, TIKI, and JNE, where JNE scored the highest as consumers' top choice. Although Pos Indonesia is trying to adapt and carry out digital transformation through the PosAja application, the reality is that the company has stagnated in recent years. The PosAja application is used by e-commerce businesses and the general public for mail and package delivery. Despite being downloaded by more than 100K+ users, the app is still facing some technical issues that have led to complaints and a drop in user ratings in recent months.

Figure 2. Category Ranking Productivity PosAja 2022
Source: AppFollow (2022)

There was a very significant drop in the productivity of the app from mid-May to June, October to November, and late December. As of December 31, 2022, the PosAja application only received a rating of 3.6 out of a total rating of 5.0, a decrease of 18% from the previous period. The rating is still below the average rating of similar applications, which reaches 3.87 (AppBrain, 2023). In this case, Pos Indonesia needs to improve the PosAja application system based on user complaints revealed through online reviews. The research method applied is the descriptive quantitative method. This study intends to identify the problems faced by PosAja application users and find the root causes. This will be used as a basis for evaluating and developing service science designs to improve user experience and satisfaction through more effective and efficient technical delivery services and applications.

METHOD

The research method applied in this study is a descriptive quantitative method that intends to provide an accurate and systematic description and explanation of the facts in the phenomenon being studied (Priadana & Sunarsi, 2021). Data collection was carried out through scraping techniques on user reviews of the PosAja application on the Google Play Store using the Appfollow analytics web-based application. To determine the sample, the purposive sampling technique is used where the sample is selected based on specific criteria so that 1,000 sample data is obtained.

Based on the scraping process, sample data consisting of 31 information attributes is obtained. Attributes that are relevant to the research are review and rating attributes, while less relevant attributes will be eliminated. The following are the results of the data selection:

Table 1. Sample Characteristics

No.	Rating	Amount	Percentage
1.	Rating 1	292	29,2%
2.	Rating 2	41	4,1%
3.	Rating 3	47	4,7%
4.	Rating 4	52	5,2%
5.	Rating 5	568	56,8%
	Total	1000	100%

Source: AppFollow

The collected data is then analyzed using text mining, SVM, and Fishbone Diagram. Support Vector Machine (SVM) is a machine learning algorithm applied to classification and regression. SVM can be applied to solve multiclass classification problems and maximize

the margin between classes separated by a hyperplane. In SVM, there are two commonly used methods, namely linear SVM and nonlinear SVM (Testiana & Erlina, 2020). When facing data that cannot be broken down linearly, SVM applies kernel functions such as Linear Kernel, Radial Basis Function (RBF) Kernel, Polynomial Kernel, and Sigmoid Kernel to convert information into a larger dimensional space. These kernel functions allow SVMs to perform classification on non-linear data.

Table 2. SVM Kernel

Kernel Functions	Equation (X_i, X_j)
Linear	$K(X_i, X_j) = X_i' X_i + c$
Radial Basis Function (RBF)	$K(X_i, X_j)$ $\exp\left(\frac{-\|\|x_i - x_j\|\|^2}{2_{a^2}}\right)$
Polynomial	$K(X_i, X_j) = (X_i' X_i + c)^p$
Sigmoid	$K(X_i, X_j) = \tanh \beta_{0x_1^T x_j} + \beta_1$

Source: Testiana & Sunarsi, 2021

Text mining is useful to help process unstructured text data into understandable and valuable information for business, research, and decision-making. Text mining techniques include text preprocessing (case folding, normalizing, tokenizing, filtering, stemming), future selection, and sentiment analysis (TF-IDF weighting, sentiment class labeling, and classification). Classification also consists of several stages which include model validation, support vector machine (SVM), optimize parameters (grid), confusion matrix, and association rules. A Fishbone Diagram is used to analyze and visualize the causes and consequences of problems in a service or product. Interpretation is done by considering factors that affect association rules, seeing cause-and-effect relationships, and understanding their contributions. The goal is to analyze the factors that cause problems based on user perceptions for evaluation or improvement of PosAja application services.

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

RESULT and DICUSSION

RESULT

SUPPORT VECTOR MACHINE (SVM) RESULTS

Sentiment Class Labeling

Sentiment labeling is done automatically using Vader Lexicon. Vader Lexicon calculates positive and negative scores for each word in the text data. In this labeling, a compound score is used to calculate the total sentiment score that includes both positive and negative connotations. The following is the sentiment class calculation through Vader Lexicon:

Table 3. Sentiment score

Review	positive	neutral	negative	compound	Result
jengkel banget kalau sistem sering error begitu perbaiki dong biar gak sering error masa cek tarif saja gagal gagal terus	0.000	0.231	0.769	-0.660	Negatives

Source: Rapidminer Data Processing Results

In sentiment labeling, the number of positive and negative words in a sentence will be counted. If negative words are more dominant, the sentence will be classified into the negative class, and vice versa. Negative reviews are given negative values, while positive words are given positive values. The labeling results show that there are 267 positive sentiment classes and 571 negative sentiment classes in the review data.

Support Vector Machine (SVM)

In this research, a cross-validation technique is used with the K-fold cross-validation method. The K-fold method will train the model using a subset of training data and test the model using k validation subsets (test data), with k=5, k=7, and k=10 used in this study. The SVM accuracy value can be seen as follows:

Table 4. Accuracy of SVM

k-fold	Accuracy SVM
k=10	88,67%
k=7	88,55%
k=5	86,75%

Source: Rapidminer Data Processing Results

SVM achieved the highest accuracy rate of 88.67% by using k=10 iterations. In addition to SVM, several other methods are also used to perform classification for comparison, as follows:

Table 5. Comparison of Classification Algorithms

Method	Accuracy		
	k=10	k=7	k=5
Support Vector Machine	88,67%	88,55%	86,75%
Naïve Bayes	77,80%	78,52%	77,92%
Random Forest	68,14%	68,14%	68,14%
Decision Tree	78,52%	78,64%	77,80%
Logistic Regression	86,53%	85,80%	86,15%

Source: Rapidminer Data Processing Results

The Support Vector Machine classification method achieved the highest level of accuracy when compared to other approaches. The next stage involves optimizing the grid parameters in the SVM model. The optimized parameters in the SVM model include linear, RBF, Sigmoid, and Polynomial kernels. Parameter optimization is done to find the optimal value of the parameters in the subprocesses, such as SVM.C, SVM.gamma, and SVM.degree. The following is the accuracy value obtained:

Table 6. Grid Parameters SVM

SVM.kernel_type	Accuracy
Linear	89,02%
RBF	89,98%
Sigmoid	89,26%
Polynomial	87,48%

Source: Rapidminer Data Processing Results

In the PosAja application review data, the RBF kernel parameter produces the highest accuracy value, which is 89.98%. The most optimal parameters are SVM.C with a value of 5.432 and SVM.gamma with a value of 0.369. Based on the best accuracy value of the kernel model, the prediction value is found using Confusion Matrix. The following is the prediction output from Confusion Matrix:

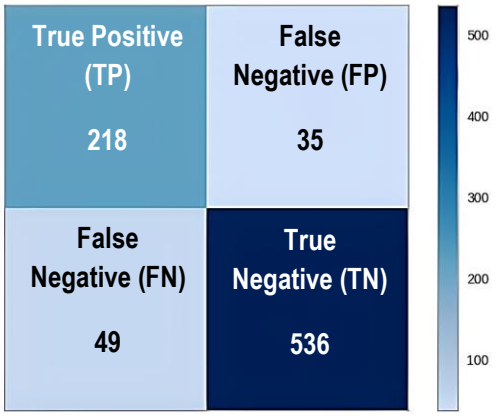

Figure 3. Confusion Matrix
Source: Google Colaboraty

In the PosAja application user review data,218 data are correctly predicted as positive sentiment classes, and 35 data are negative but incorrectly predicted as positive sentiment classes. In addition, there are 536 536 data aredictedpredictedive sentiment classes and 49 data that are actually but wrongly predicted as negative sentiment classes. Confusion Matrix is also used to calculate SVM model evaluation measures, including accuracy, standard deviation, recall, precision, and F1 score. The following are the model evaluation values with SVM:

Table 7. Evaluation Model SVM

Dimensions	Scores
Accuracy	89,98%
Standard deviation	2,91%
Recall/sensitivity	81,65%
Precision	86,17%
F1 Score	83,85%

Source: Rapidminer Data Processing Results

Association Rules

Association Rules are used to discover patterns and relationships between frequently co-occurring words in review data, to enhance information retrieval, and predict the root cause of the topic of conversation. Association rules consist of two parts, namely antecedent (if) and consequent (then), which express the relationship between items or sets of items in the data. Association rules are created by deciphering frequent patterns in the data and applying support, confidence, and lift ratio as criteria to identify important relationships. Here are the results of the association rules found:

Table 8. Association Rules

Premises	Conclusion	Support	Confidence	Elevator
Send	bad	0.025	0.082	1,461
Send	no, item	0.025	0.082	2,337
Send	arrive, serve	0.025	0.082	2,337
Send	come on, use it	0.025	0.082	2,922
Send	accept	0.026	0.088	1,431
Send	service	0.026	0.088	2,504
Send	arrived, package	0.026	0.088	1,789
Send	Indonesia	0.028	0.094	1,370
Send	slow	0.030	0.099	2,183

Send	disappointed	0.033	0.111	2,047
Send	arrived, goods	0.035	0.117	2,385
Send	application	0.039	0.129	0.693
Send	use	0.039	0.129	1,530
No	send goods	0.025	0.131	2,197
application	posaja	0.025	0.132	2,285
application	enter	0.026	0.142	1,757
No	enter	0.028	0.150	1,856
until	long	0.025	0.152	1,889
until	send, serve	0.025	0.152	2,896
until	send, use	0.025	0.152	3,950
No	serve	0.030	0.159	1,243
until	send, package	0.026	0.163	2,271
Send	until, day	0.049	0.164	2,527
until	use	0.028	0.174	2,069
until	package, day	0.028	0.174	4,318
Send	serve	0.053	0.175	1,372
No	day	0.033	0.178	1,662
Send	long	0.054	0.181	2,250
package	serve	0.026	0.183	1,431
package	accept	0.026	0.183	2,984
package	send, arrive	0.026	0.183	1,801
No	goods	0.035	0.187	1,809
serve	send, arrive	0.025	0.192	1,888
package	until, day	0.028	0.195	3,011
Send	goods	0.060	0.199	1,924
serve	package	0.026	0.205	1,431
serve	bad	0.026	0.205	3,667
No	until	0.039	0.206	1,276
application	Send	0.039	0.208	0.693
until	serve	0.035	0.217	1,700
until	send goods	0.035	0.217	3,651
Send	day	0.068	0.228	2,135
serve	No	0.030	0.233	1,243
Send	No	0.070	0.234	1,248
goods	send, no	0.025	0.237	3,387
until	No	0.039	0.239	1,276
Send	package	0.072	0.240	1,670
send, arrive	serve	0.025	0.241	1,888
send, arrive	use	0.025	0.241	2,871
No	package	0.046	0.243	1,692
send, arrive	package	0.026	0.259	1,801
day	arrived, package	0.028	0.262	5,349

serve	until	0.035	0.274	1,700
package	day	0.040	0.280	2,626
goods	accept	0.030	0.288	4,701
No	application	0.054	0.290	1,561
use	send, arrive	0.025	0.292	2,871
application	No	0.054	0.292	1,561
until	package	0.049	0.304	2,119
until	goods	0.049	0.304	2,945
long	until	0.025	0.304	1,889
until	send, day	0.049	0.304	4,456
day	No	0.033	0.311	1,662
package	No	0.046	0.317	1,692
enter	application	0.026	0.326	1,757
use	until	0.028	0.333	2,069
goods	No	0.035	0.339	1,809
goods	send, arrive	0.035	0.339	3,337
Send	until	0.102	0.339	2,105
package	until	0.049	0.341	2,119
send, arrive	goods	0.035	0.345	3,337
enter	No	0.028	0.348	1,856
send, no	goods	0.025	0.350	3,387
send, package	until	0.026	0.366	2,271
No	Send	0.070	0.374	1,248
day	package	0.040	0.377	2,626
until	day	0.065	0.402	3,765
Indonesia	Send	0.028	0.410	1,370
serve	Send	0.053	0.411	1,372
send goods	No	0.025	0.412	2,197
posaja	application	0.025	0.424	2,285
accept	Send	0.026	0.429	1,431
accept	package	0.026	0.429	2,984
until, day	package	0.028	0.432	3,011
bad	Send	0.025	0.438	1,461
use	Send	0.039	0.458	1,530
day	send, arrive	0.049	0.459	4,519
send, serve	until	0.025	0.467	2,896
bad	serve	0.026	0.469	3,667
goods	until	0.049	0.475	2,945
send, arrive	day	0.049	0.483	4,519
accept	goods	0.030	0.486	4,701
package	Send	0.072	0.500	1,670
Help	repair	0.025	0.500	11,896
arrived, package	Send	0.026	0.536	1,789

arrived, package	day	0.028	0.571	5,349
goods	Send	0.060	0.576	1,924
repair	Help	0.025	0.583	11,896
send goods	until	0.035	0.588	3,651
day	until	0.065	0.607	3,765
disappointed	Send	0.033	0.613	2,047
until	Send	0.102	0.630	2,105
send, use	until	0.025	0.636	3,950
day	Send	0.068	0.639	2,135
verification	code	0.032	0.643	13,595
slow	Send	0.030	0.654	2,183
code	verification	0.032	0.667	13,595
long	Send	0.054	0.674	2,250
package, day	until	0.028	0.696	4,318
no, item	Send	0.025	0.700	2,337
arrive, serve	Send	0.025	0.700	2,337
arrived, goods	Send	0.035	0.714	2,385
send, day	until	0.049	0.718	4,456
service	Send	0.026	0.750	2,504
until, day	Send	0.049	0.757	2,527
come on, use it	Send	0.025	0.875	2,922

Source: Rapidminer Data Processing Results

The word cloud visualization displays a collection of negative words that frequently appear in the review data, based on the results of association rules. Here is a word cloud visualization that displays these words:

Figure 4. Word Cloud
Source: WordArt

The results of the association rules process and the word clouding process show that the antecedents or keywords of the main complaints of the PosAja application users are “kirim”, “tidak”, “aplikasi”, “sampai”, “paket”, “layan”, “hari”, “barang”, “pakai”, “lama”, “masuk”, “Indonesia”, “terima”, “posaja”, “buruk”, “kecewa”, “tolong”, “verifikasi”, “kode”, “lambat”, “perbaiki” and “jasa”. The antecedent can be reinterpreted in the diagram to knowing one diagram to know what to do to overcome the problem. The following is a form of interpreting the fishbone diagram.

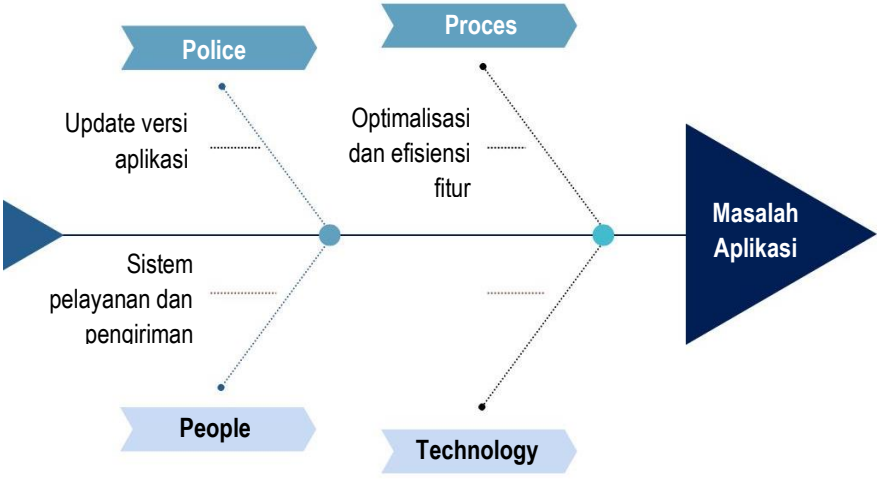

Figure 5. Fishbone Diagram
Source: Association Rules

Based on the fishbone diagram, it can be seen that the problems that are often complained about by users of the PosAja application owned by Pos Indonesia include:

Police

Improvements that need to be made to the PosAja application include a better update policy, updates to the main page, bug handling, and improvements to the referral code. There were several issues related to the login process, such as long loading times and failure to open the app. In addition, users also faced issues with app updates requiring them to re-login and not being able to use previously used account information. The security system also faced issues detecting changes in device IDs, resulting in temporarily blocked access and requiring recovery through customer service. Another problem encountered was related to referral codes or verification codes that did not appear despite repeated logins, so users could not enter the main page of the application and were stuck on the registration menu.

Process or Service Process

There are sever Several features in the PosAja application experience are not yet optimal. For example, the tariff checking and delivery tracking features often experience errors. In addition, regional codes, QR codes, and receipt numbers are also not detected properly. Users must manually check through the Pos Indonesia website. In shipping goods, users cannot download the receipt directly through the app, so they have to print it manually through the website. Delivery history is also automatically deleted, which requires users to re-enter information when making repeat purchases. The user points feature does not increase when placing delivery orders, and voucher claims cannot be used properly.

Several problems also occur with the payment features in the PosAja application. These include delivery payments, COD (Cash on Delivery), and foreign exchange tax payments. The payment system only accepts Giro Pos, while it does not allow users to use government or private bank accounts. COD couriers are also not responsible for depositing COD money when the package is received by the user. In addition, the payment method system has also experienced problems, such as failure to pay foreign exchange tax, errors during the payment process, and payment methods that are not user-friendly.

People or Human Role

Several problems often arise in delivery services involving Pos Indonesia, Couriers, and Pos Indonesia O-Ranger Partners. One of the complaints that is often expressed is the delay in the pick-up process and inaccurate delivery estimates. Users often have to wait without getting clear confirmation of the pickup of goods and find it difficult to contact the center number of O-Ranger. Delivery estimates often exceed the set time limit, causing users to experience losses both in terms of time and material. time and material losses. Pos Indonesia's response to user complaints about the position of delivered goods was also unsatisfactory. Other problems include redelivery, package returns/reject, and inaccuracies in receipt status. Couriers often deliver packages to the wrong address or state that the goods have been received by someone else. In addition, Pos Indonesia also does not provide material compensation for lost packages. While delivery companies should be liable for losses suffered by users, certain limitations restrict their liability, especially if caused by force majeure circumstances.

DISCUSSION

Customer experience is a key focus for several companies, including Pos Indonesia. After launching the app, it is important to continuously monitor and update based on user feedback and changing market needs to maintain user satisfaction. Developing application service science design through customer experience is an ongoing process. This development opens up great opportunities to innovatively improve the user experience. Artificial Intelligence (AI) as one of the aspects of service science in this case cannot be ignored. AI has various roles according to the needs of the application and the context in which it is used. In this research, AI plays an important role in the operational management of the application and the processing and analysis of user feedback or review data.

In the operational management of the app, AI plays an important role in automating processes using Machine Learning (ML) and Robotic Process Automation (RPA) techniques. This helps reduce dependency on manual work, improves operational efficiency, and enables AI to analyze data in real time through Natural Language Processing (NLP) and predictive analytics. In addition, AI plays a role in optimizing application performance and operational efficiency, as well as predicting future application capacity requirements through analysis of user operational data, including bandwidth, to better advise on corrective actions. By processing and analyzing customer experience data, operations teams gain valuable information to improve products or services, identify areas of improvement, launch new features, or even personalize the customer experience, ultimately improving overall customer satisfaction.

AI's role in data processing and analysis includes its ability to help collect, manage, and analyze large and complex data quickly and efficiently. Through machine learning methods, AI can identify patterns, trends, and valuable information from application operational data. This helps make better decisions in optimizing production processes, developing new features, or even improving application quality. This information is also useful for understanding customer needs and providing customized experiences. Moreover, with its ability to analyze data, understand human language, recognize images and sounds, and automate tasks, AI provides great potential to make apps smarter, responsive, and adaptive to user needs. In some cases, AI also helps improve the efficiency, quality, and reliability of applications. AI also plays a role in training machine learning models, which use algorithms and statistical models to teach apps to learn from data and make intelligent predictions or decisions.

Based on such sentiment analysis, predictive analysis, and review classification, user participation and experience in app development and improvement is important to understand user needs, preferences, and expectations. Developing an app that meets user needs involves well-coordinated backend and frontend components. Optimized app

performance creates a positive user experience with fast load times, instant response and smooth navigation without bugs. Developers must continuously improve user experience and adapt to changing market needs to maintain optimal performance. Meanwhile, the development of service science design in addressing delivery issues requires open communication with partners and customers. It is important to ensure communication channels are easily accessible, proactively provide relevant information, and be responsive to customer queries and complaints. Improved tracking and estimation systems, as well as automatic notifications in case of delays, are important steps in maintaining service reliability and efficiency. Evaluation of delivery partners based on service quality is a concern in continuous improvement efforts. A thorough assessment of partner and non-partner services is conducted to improve services and consider other options if necessary.

Good e-service quality can be assessed through efficiency, fulfillment of needs, system availability, and privacy. By referring to this value, the quality of service and performance on the application system and service system will be more optimal and good so that it can improve a better user experience. A good user experience tends to make users feel more satisfied with a product or service. User satisfaction itself is a person's feeling of pleasure or disappointment after comparing the performance of a product with his expectations which refers to user satisfaction. There are three main components related to user satisfaction, namely response, focus, and response time (Grifin in Nasruddin, 2023).

CONCLUSION

The results of analyzing PosAja application review data using Support Vector Machine (SVM), Association Rules, and fishbone diagrams reveal three main factors that cause user complaints, namely policies (application version updates), processes (suboptimal service features), and people (service systems during the delivery process). In developing a service science design for the PosAja application, the important role of Artificial Intelligence (AI) can be utilized in application operational management and processing user review data. AI enables real-time monitoring of application performance, optimization of application operational efficiency, and prediction of future application capacity requirements by analyzing user operational data. In review data processing, AI uses SVM machine learning techniques to improve classification, sentiment analysis, and review data processing tasks.

Service science design development can involve in-depth solutions to internal backend systems by Pos Indonesia developers related to servers, clouds, and databases in the PosAja application. Improvements can also be made to the front end of the application to create a good user experience and achieve a more optimized, effective, efficient, and user-friendly application. Optimized application performance not only improves user satisfaction, but also impacts growth, user retention, and the overall image of the application. In this context, it is important to identify and adjust server capacity proportionally according to the number of users and application traffic.

Improvements in the delivery service system can be made through system upgrades, automation, system integration, and evaluation of employee skills, improved communication with customers and internal teams, and continuous performance feedback and evaluation.

Future research can explore ensemble methods such as SVM with voting strategies or combination with deep learning models such as neural networks to improve sentiment prediction. Also, exploration of better feature extraction methods such as the use of word embeddings or more advanced natural language processing techniques such as integration of SVM with unsupervised learning methods such as k-means clustering or Latent Dirichlet Allocation (LDA) can provide deeper insights into sentiment. In addition, future research can focus on handling sentiment class imbalance by developing oversampling,

undersampling, or other approaches such as SMOTE to improve SVM's performance in classifying sentiment in minority classes.

REFERENCES

AppBrain. (2023, February 26). Android Statistics - Top categories. Diambil kembali dari AppBrain: https://www.appbrain.com/stats/android-market-app-categories

Asosiasi Penyelenggara Jasa Internet Indonesia (APJII) . (2022).

Bascur, C., & Rusu, C. (2020). Customer Experience in Retail: A Systematic Literature Review. MDPI Applied Sciences, 1-18.

Bolton, R. N. (2019). Service Timing: Designing and Executing Service in a Dynamic Environment. Dalam P. P. Maglio, C. A. Kieliszewski, J. C. Spohrer, K. Lyons, L. Patrício, & Y. Sawatani, Service Science: Research and Innovations in the Service Economy (hal. 13-34). Switzerland: Springer Nature Switzerland.

Dorsey, M., Temkin, B., & Quaadgras, T. (2022). The State of CX Management. Qualtrics XM Institute.

Grifin in Nasruddin, R. M. (2023). Pengaruh Service Quality terhadap Customer Satisfaction pada Layanan Jasa Go-Jek di Kota Palopo. Jurnal Manajemen Perbankan Keuangan Nitro (JMPKN), 26-38.

Hasibuan, E., & Heriyanto, E. A. (2022). Analisis Sentimen pada Ulasan Aplikasi Amazon Shopping di Google Play Store Menggunakan Naive Bayes Classifier. Jurnal Teknik dan Science, 13-24.

Holmlund, M., Vaerenbergh, Y. V., Ciuchita, R., Ravald, A., Sarantopoulos, P., Ordenes, F. V., & Zaki, M. (2020). Customer Experience Management in The Age of Big Data Analytics: A Strategic Framework. Journal of Business Research, 356-365.

Luigi Cantone, P. T. (2019). Service-Dominant Logic: Inward and Outward Views. Dalam P. P. Maglio, C. A. Kieliszewski, J. C. Spohrer, K. Lyon, L. Patrício, & Y. Sawatani, Service Science: Research and Innovations in the Service Economy (hal. 675-710). Switzerland: Springer Nature.

Maglio, P. P., Kieliszewski, C. A., Spohrer, J. C., Lyons, K., Patrício, L., & Sawatani, Y. (2019). Service Science: Research and Innovations in the Service Economy. Switzerland: the registered company Springer Nature.

Permana, H., & Djatmiko, T. (2018). Analisis Pengaruh Kualitas Layanan Elektronik (E-Service Quality) terhadap Kepuasan Pelanggan Shopee di Bandung. SOSIOHUMANITAS, 201-2015.

Prasuraman et al in Hizam, S. M., & Ahmed, W. (2019). A Conceptual Paper on SERVQUAL-Framework for Assesing Quality of Internet of Things (IoT) Service. International Journal of Financial Research, 387-397.

Priadana, S., & Sunarsi, D. (2021). Metode Penelitian Kuantitatif. Indonesia: Pascal Books.

Putro, H. P., Widyaningsih, T. W., Englishtina, I., Nursanty, E., Efitra, Sepriano, & Dema, H. (2023). Development Of Artificial Intelligence Applications (Studi Kasus & Implementasi AI Menggunakan Berbagai Bahasa Pemrograman). Indonesia: PT Sonpedia Publishing Indonesia.

Revika, N. R., & Handayani, W. (2022). Desain Service Science untuk Meningkatkan Kepuasan. BRILIANT: Jurnal Riset dan Konseptual, 841-852.

Rogerson, A., Hankins, E., Nettel, P. F., & Rahim, S. (2022). Government AI Readiness Index 2022. Oxford Insight.

Sartika, S. H., Murdana, I. M., Permadi, L. A., Sudarso, A., Purba, A. T., Sahir, S. H., . . . Fajrillah. (2023). Customer Relationship Management. Indonesia: Yayasan Kita Menulis.

Testiana, G., & Erlina, D. (2020). Analisis Sentimen pada Twitter terhadap UIN Raden Fatah Menggunakan Support

Vector Machine. Indonesia: Rafah Press.

Tresnawati, D., Guno, Y., Satwika, I. P., Prihatmanto, A. S., & Mahayana, D. (2022). Artificial Intelligence serta Singularitas Suatu Kekeliruan atau Tantangan. Jurnal Algoritma, 181-188.

Venkatesh, V., Afuang, A., Rago, T., Carreon, M., Gupta, V., & Cai, J. D. (2022, April 6). Asia/Pacific* Artificial Intelligence Spending to Reach $32 Billion in 2025, Says IDC. Diambil kembali dari IDC Media Center: https://www.idc.com/getdoc.jsp?containerId=prAP49010122

Zein, A. (2021). Kecerdasan Buatan Dalam Hal Otomatisasi Layanan. Jurnal Ilmu Komputer, 16-25.