Analysis of Customer Feedback for an E-Commerce Application Based on Artificial Neural Networks

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Abstract—With the rise of the Internet, e-commerce platforms have become one of the primary shopping channels for consumers. Establishing an efficient and intelligent customer service system is a crucial challenge for these platforms. This research aims to analyze how the interactivity of e-commerce applications and customer feedback from online shopping experiences can influence consumer loyalty and the likelihood of repurchasing. To evaluate customer loyalty, we utilize an artificial neural network processed using the SPSS application. The findings indicate that the relationship between interactivity, consumer feedback, and loyalty has a confidence level of 85.4%. A relationship between variables is considered strong if the R-squared value is above 50%, while a value below 50% indicates a weaker relationship.

Keywords—E-Commerce, Artificial Neural Network, Loyalitas Customer, Feedback Customer

I. INTRODUCTION

The development of information technology, coupled with the ongoing impacts of the COVID-19 pandemic, has led to a rise in online consumers engaging in both shopping and selling on e-commerce platforms. The conditions for shopping and selling in e-commerce are designed to make transactions safe and convenient [1],[2]. By shopping online, customers can easily access detailed information about the items they wish to purchase and can communicate directly with sellers. Meanwhile, sellers (retailers) can provide comprehensive details about the products or services they offer in e-commerce [1],[2].

The rise of the internet has made e-commerce platforms a primary shopping channel for consumers [3],[4]. Developing an efficient and intelligent customer service system is a challenge that e-commerce platforms must address [5],[6],[7],[8],[9]. Feedback on e-commerce marketplaces has become increasingly popular, as this method helps customers efficiently purchase products or services. With the rise of e-commerce, the feedback received varies significantly. Therefore, it is essential to understand the factors that influence customers to provide feedback on these online platforms [6].

In this article, we will discuss the factors influencing consumer behavior when purchasing goods and services through e-commerce in Indonesia. Specifically, we will focus on interactivity within applications and the importance of customer feedback. Interactivity refers to the degree to which users can engage with virtual content or objects, as well as their ability to modify the format or content of the digital environment.[10]. High interactivity indicates that consumers engage with retail mobile applications[3], even while physically present in a room. Their minds are in a virtual space, where these applications—whether on mobile devices or websites—allow consumers to actively control their experience. Users can touch, rotate, zoom in, and zoom out on products within this virtual space, mimicking the actions they take when shopping in physical stores [10],[11],[12]. Based on previous research, interactivity, application performance, and customer feedback influence repurchase interest in e-commerce [13],[14],[15],[16]. So in this research, a survey will be conducted on 100 respondents to see how much influence customer loyalty has on purchasing via e-commerce.

II. METHODOLOGY

A. Research Framework

Before entering into a discussion of methodology in research, in this article, the variables used in research are mentioned as follows:

a. Interactivity

The interactivity discussed here involves defining the independent variables used as assessment parameters. By rotating, zooming, or pinching a virtual product, the consumer's imagination is both facilitated and enhanced during a detailed examination of the product [17]. Furthermore, consumers can interact with nearby service providers and other users through chat boxes or online reviews, receiving immediate responses from relevant retail mobile applications [18]. Interactive design features enable consumers to participate in an embodied cognition process. In this process, they imagine themselves within a virtual mobile application and can perform various actions. As a result, they experience a sense of spatial presence within the virtual retail mobile application [19].

b. Customer Feedback

The customer feedback mentioned here defines the dependent variable used for parameter assessment. Customer feedback refers to the information provided by customers about their experiences with services and interactions [4] during buying and selling transactions, specifically in the context of online transactions through e-commerce [20].

c. Customer Loyalty

Customer loyalty is treated as an intervening variable here. Loyalty to a retailer signifies a customer's preference to choose that retailer first [21], Engage more with the retailer, leave positive feedback, and recommend their services to others [22]. Satisfied customers are less likely to switch service providers and are more inclined to repeat transactions with the same outlet [23]. They are also less likely to seek additional information and explore competitors' offerings [24]. Previous research has shown that customers' online experiences with e-services can significantly affect their satisfaction and foster loyalty towards the service provider [23],[25]. Research indicates that customer satisfaction with retailer applications positively affects their loyalty to those retailers.

In this study, there are five variables: three independent variables, one dependent variable, and one intervening variable. Figure 1 below illustrates the research design and conceptual framework.

Figure 1. Research framework

B. Population and Sample

The population for this research consists of e-commerce application users aged 18 to 50 years. The sample includes e-commerce application users residing in the Bekasi district. The data collection period is from December 16, 2023, to January 6, 2024, with a total of 100 respondents participating in the study. A nonprobability sampling method, specifically purposive sampling, was employed for sample selection. Data was gathered through questionnaires distributed via Google Forms. For data processing and analysis, the neural network algorithm was utilized, using the SPSS application.

Table 1. Respondent Description

Characteristic	Classification	Frequency	Percentage
Gender	Male	27	27.00%
	Female	73	73.00%
	Total	100	100.00%
Age	Under 17	2	2.00%
	18 to 30	71	71.00%
	31 to 40	19	19.00%
	41 to 50	8	8.00%
	50 or above	0	0.00%
	Total	100	100.00%
Latest of Education	SD	1	1.00%
	SMP	2	2.00%
	SMA/SMK/High School Equivalent	30	30.00%
	Diploma	13	13.00%
	Strata 1 (S1)	48	48.00%
	Strata 2 (S2)	6	6.00%
	Strata 3 (S3)	0	0.00%
	Total	100	100.00%
Job	student/College Student	28	28.00%
	Employee	33	33.00%
	Civil Servant	15	15.00%
	Self-Employed	14	14.00%
	Labor	1	1.00%
	Lecture/Teacher/Tutor	5	5.00%
	Professional	1	1.00%
	House Wife/Husband	3	3.00%
	Retirement	0	0.00%
	Total	100	100.00%
Income	<IDR. 1.000.000	30	30.00%
	IDR. 1.000.000 b/w . IDR. 2.500.000	27	27.00%
	IDR. 2.500.000 b/w. IDR. 5.000.000	25	25.00%
	IDR. 5.000.000 b/w . IDR7.500.000	10	10.00%
	>IDR. 7.500.000	8	8.00%
	Total	100	100.00%
Device	Cell Phone	91	91.00%
	Tablet/iPad	4	4.00%
	laptop	5	5.00%
	Total	100	100.00%

C. Likert Scale

The Likert scale is a method used to gauge user satisfaction. [26]. The Likert scale was created by Rensis Likert in 1932. It uses a set of choices and score values for favorable statements. :

1. Strongly Disagree (Score 1)
2. Disagree (Score 2)
3. Don't Know (Score 3)
4. Agree (Score 4)
5. Strongly Agree (Score 5)

D. Neural Network

An Artificial Neural Network, commonly referred to as a neural network, is an information processing method that mimics the performance characteristics of human biological neural networks. Researchers often utilize neural networks for analysis because they do not require specific assumptions about the data, which can often be challenging to meet [27],[28],[29],[30],[31],[32],[33]. Neural networks are viewed as statistical methods that are both nonlinear and nonparametric [34], [35]. Neural networks, trained on sample data, can make inferences about unknown aspects of a population. This principle aligns with the concepts of prediction and forecasting, where future conditions are anticipated based on past data (samples). Neural networks are often described as universal function approximators, as they can demonstrate this capability effectively [36] The neural network approximates a continuous function with the desired level of accuracy [37],[38],[39],[40]. Forecasting or prediction models typically describe the functional relationship between inputs and outputs. In complex systems, traditional statistical methods often struggle to accurately estimate these functions, making neural networks a suitable alternative. Below, Figure 2 illustrates the performance of neural networks.

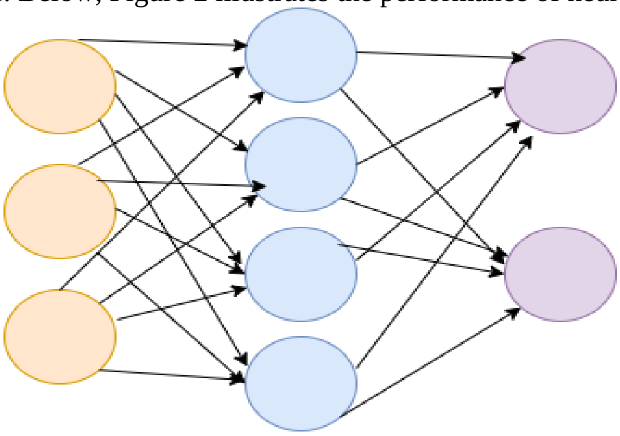

Figure 2. Illustration of Artificial Neural Network Performance

III. Research Result

A. Case Processing Summary

The Case Processing Summary image provides an overview of whether any data was lost during the data processing stage in the SPSS analysis application. According to this summary, 100% of the data was included in the processing. Of this data, 70% was allocated for training purposes, while the remaining 30% was set aside for testing.

Case Processing Summary

		N	Percent
Sample	Training	70	70.0%
	Testing	30	30.0%
Valid		100	100.0%
Excluded		0	
Total		100	

Figure 3. *Case Processing Summary*

B. Network Information

Figure 4 shows network information derived from the processed data, highlighting the dependent information and influencing factors.

a. Dependent

The influencing factor is the interactivity variable which is symbolized by px. The detailed information on the questionnaire questions is as follows:

1. When I use a retail mobile app, I can easily choose what I want to see.
2. Retail mobile apps enable two-way communication between retailers and their consumers.
3. Retail mobile apps do not encourage visitors to provide feedback at all.
4. The retail mobile app processes my input very quickly.
5. I can obtain information from the retail mobile app very quickly.
6. When I click on a retail mobile app, I feel like I receive the instant information I expect.
7. I feel like I have a lot of control over my experience with retail mobile apps.
8. Retail mobile apps give me the impression that retailers want to listen to their

b. Customer.Factors

The factor symbolized by the symbol cx is the customer feedback variable. The detailed information on the questionnaire questions is as follows:

1. When I encounter issues with a retail mobile app, I give feedback to the retailer about my experience.
2. I offer suggestions and complete surveys to help improve the performance of retail mobile apps.
3. I share my feedback and suggestions on new features for retail mobile apps.
4. I provide input and ideas for developing new functionalities in the retail mobile app.

Network Information

Input Layer	Factors	1	cx1
		2	cx2
		3	cx3
		4	cx4
		5	cxtotal
	Number of Units[a]		34
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		20
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	px1
		2	px2
		3	px3
		4	px4
		5	px5
		6	px6
		7	px7
		8	px8
		9	pxtotal
	Number of Units		41
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Figure 4. Result in Network Information

C. Network Diagram

In Figure 5 below, a network diagram is presented, illustrating the visualization of a project or production based on network planning. This diagram provides an overview of the work network, showcasing the activity trajectories and sequences of events that occur during project implementation or the completion of production. It is designed to aid in making predictions based on the processed variables., namely px and cx.

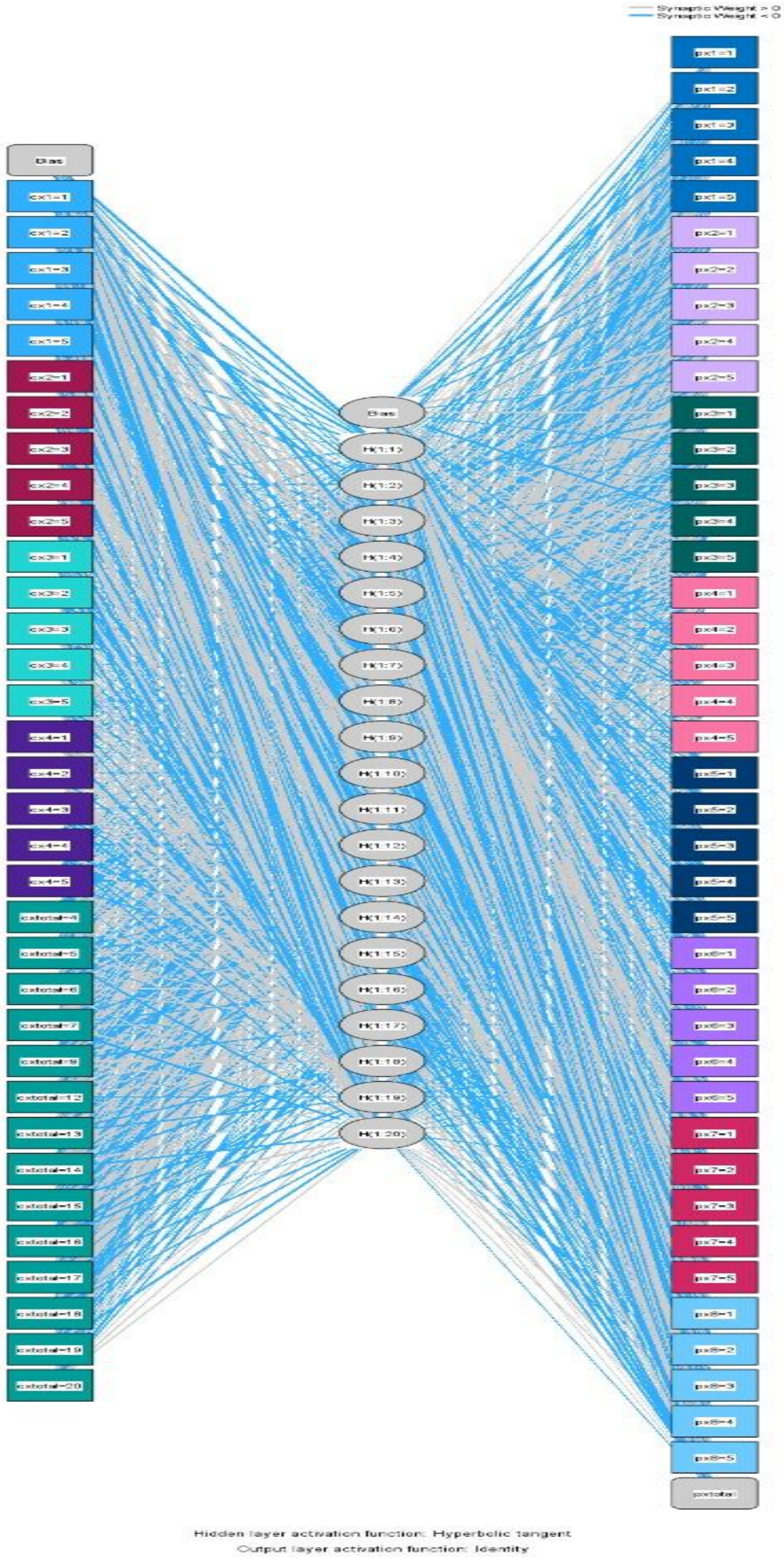

Figure 5. Network visualization using the neural network method

D. Model Summary

Figure 6 below illustrates the results of the summary model, which aims to determine the relationship between two or more variables in the regression equation. The R-squared value in the results is 85.448, or 85.4%. This indicates that the influence of interactivity (px) on customer feedback is 85.4%. An R-squared value above 50% indicates a good relationship between variables, while a value below 50% suggests a poor relationship.

Model Summary

Training	Sum of Squares Error		142.539
	Average Overall Relative Error		.636
	Percent Incorrect Predictions for Categorical Dependents	px1	37.1%
		px2	32.9%
		px3	28.6%
		px4	45.7%
		px5	37.1%
		px6	27.1%
		px7	28.6%
		px8	28.6%
	Relative Error for Scale Dependents	pxtotal	.291
	Stopping Rule Used		1 consecutive step(s) with no decrease in error[a]
	Training Time		0:00:00,08
Testing	Sum of Squares Error		85.448
	Average Overall Relative Error		.914
	Percent Incorrect Predictions for Categorical Dependents	px1	53.3%
		px2	43.3%
		px3	43.3%
		px4	60.0%
		px5	36.7%
		px6	46.7%
		px7	46.7%
		px8	50.0%
	Relative Error for Scale Dependents	pxtotal	.420

a. Error computations are based on the testing sample.

Figure 6. Visualization of Summary model results

E. Classification

The following is a description of an image illustrating the classification results of each pixel variable (denoted as px) alongside the percentages obtained from a questionnaire. The px variable represents an interactive activity that reflects the consumer's experience when using e-commerce applications based on their shopping habits.

a. Px1

In the case of px1, as shown in Figure 7, we can see information about both training data and test data for dimension 1. The interactivity percentage for the training data is 62.9%, while for the test data, it stands at 46.7%.

px1

Sample	Observed	Predicted STS	TS	N	S	SS	Percent Correct
Training	STS	3	0	0	3	2	37.5%
	TS	0	3	0	0	0	100.0%
	N	0	0	4	2	3	44.4%
	S	1	0	1	18	6	69.2%
	SS	0	0	1	7	16	66.7%
	Overall Percent	5.7%	4.3%	8.6%	42.9%	38.6%	62.9%
Testing	STS	0	0	0	1	1	0.0%
	TS	1	1	0	0	1	33.3%
	N	0	0	2	2	0	50.0%
	S	0	1	3	7	3	50.0%
	SS	0	0	0	3	4	57.1%
	Overall Percent	3.3%	6.7%	16.7%	43.3%	30.0%	46.7%

Figure 7. Dimension 1 interactivity variable

b. Px2

Below, Figure 8, namely px2, displays information on training data and test data in dimension 2, the interactivity variable of training data is 67.1% and test data is 56.7%.

px2

Sample	Observed	Predicted STS	TS	N	S	SS	Percent Correct
Training	STS	1	1	0	0	1	33.3%
	TS	0	3	0	1	0	75.0%
	N	1	0	1	2	4	12.5%
	S	0	0	0	9	7	56.3%
	SS	0	0	0	6	33	84.6%
	Overall Percent	2.9%	5.7%	1.4%	25.7%	64.3%	67.1%
Testing	STS	1	1	0	0	1	33.3%
	TS	0	0	0	0	0	0.0%
	N	0	0	0	1	2	0.0%
	S	0	0	0	6	5	54.5%
	SS	0	0	0	3	10	76.9%
	Overall Percent	3.3%	3.3%	0.0%	33.3%	60.0%	56.7%

Figure 8. Dimension 2 interactivity variable

c. Px3

Figure 9, referred to as px3, presents data on training and testing in dimension 3. The interactivity percentage for the training data is 71.4%, while for the test data, it is 56.7%.

px3

		Predicted					
Sample	Observed	STS	TS	N	S	SS	Percent Correct
Training	STS	2	0	0	1	1	50.0%
	TS	0	2	0	0	0	100.0%
	N	0	0	1	7	0	12.5%
	S	1	0	0	22	5	78.6%
	SS	0	0	0	5	23	82.1%
	Overall Percent	4.3%	2.9%	1.4%	50.0%	41.4%	71.4%
Testing	STS	0	0	0	0	0	0.0%
	TS	1	1	0	0	0	50.0%
	N	0	0	0	3	0	0.0%
	S	0	0	0	9	3	75.0%
	SS	0	0	0	6	7	53.8%
	Overall Percent	3.3%	3.3%	0.0%	60.0%	33.3%	56.7%

Figure 9. Dimension 3 interactivity variable

d. Px4

Figure 10, labeled px4, shows the training and test data in dimension 4. The interactivity variable for training data is 54.3%, while for test data it is 40.0%.

px4

		Predicted					
Sample	Observed	STS	TS	N	S	SS	Percent Correct
Training	STS	4	0	0	2	3	44.4%
	TS	1	1	0	7	4	7.7%
	N	0	0	2	6	1	22.2%
	S	0	0	0	22	3	88.0%
	SS	0	0	0	5	9	64.3%
	Overall Percent	7.1%	1.4%	2.9%	60.0%	28.6%	54.3%
Testing	STS	0	0	1	2	2	0.0%
	TS	0	0	1	1	0	0.0%
	N	0	0	0	4	1	0.0%
	S	0	0	0	11	4	73.3%
	SS	0	0	0	2	1	33.3%
	Overall Percent	0.0%	0.0%	6.7%	66.7%	26.7%	40.0%

Figure 10. Dimension 4 interactivity variable

e. Px5

Figure 11, labeled px5, presents information on the training and test data in dimension 5. The interactivity variable for the training data is 62.9%, while for the test data it is 63.3%.

px5

Sample	Observed	Predicted STS	TS	N	S	SS	Percent Correct
Training	STS	1	0	0	1	1	33.3%
	TS	0	2	0	1	0	66.7%
	N	0	0	2	10	2	14.3%
	S	0	0	1	21	7	72.4%
	SS	0	0	0	3	18	85.7%
	Overall Percent	1.4%	2.9%	4.3%	51.4%	40.0%	62.9%
Testing	STS	0	1	0	1	0	0.0%
	TS	0	0	0	0	0	0.0%
	N	0	0	1	4	1	16.7%
	S	0	0	0	13	2	86.7%
	SS	0	0	0	2	5	71.4%
	Overall Percent	0.0%	3.3%	3.3%	66.7%	26.7%	63.3%

Figure 11. Dimension 5 interactivity variable

f. Px6

Figure 12, referred to as px6, shows information on training and test data in dimension 6. The interactivity variable for the training data is 72.9%, while it is 53.3% for the test data.

px6

Sample	Observed	Predicted STS	TS	N	S	SS	Percent Correct
Training	STS	0	0	0	1	1	0.0%
	TS	0	4	0	0	1	80.0%
	N	0	1	3	3	1	37.5%
	S	0	0	1	20	4	80.0%
	SS	0	0	1	5	24	80.0%
	Overall Percent	0.0%	7.1%	7.1%	41.4%	44.3%	72.9%
Testing	STS	0	0	0	0	0	0.0%
	TS	0	1	1	1	0	33.3%
	N	0	0	0	6	1	0.0%
	S	0	0	0	9	2	81.8%
	SS	0	0	0	3	6	66.7%
	Overall Percent	0.0%	3.3%	3.3%	63.3%	30.0%	53.3%

Figure 12. Dimension 6 interactivity variable

g. Px7

Figure 13, labeled px7, shows the training and test data in dimension 7. The interactivity variable for the training data is 71.4%, while for the test data it is 53.3%.

px7

Sample	Observed	Predicted STS	TS	N	S	SS	Percent Correct
Training	STS	2	0	0	0	0	100.0%
	TS	0	4	0	0	0	100.0%
	N	0	0	1	3	1	20.0%
	S	0	0	0	18	8	69.2%
	SS	0	0	0	8	25	75.8%
	Overall Percent	2.9%	5.7%	1.4%	41.4%	48.6%	71.4%
Testing	STS	0	0	0	0	0	0.0%
	TS	1	1	0	1	0	33.3%
	N	0	0	0	3	0	0.0%
	S	0	0	0	7	3	70.0%
	SS	0	0	0	6	8	57.1%
	Overall Percent	3.3%	3.3%	0.0%	56.7%	36.7%	53.3%

Figure 13. Dimension 7 interactivity variable

h. Px8

Figure 14, referred to as px8, presents information on training and test data in dimension 8. The interactivity variable for the training data is 71.4%, while for the test data, it is 50.0%.

px8

Sample	Observed	Predicted STS	TS	N	S	SS	Percent Correct
Training	STS	3	0	0	0	0	100.0%
	TS	0	2	0	0	0	100.0%
	N	0	1	4	2	2	44.4%
	S	0	0	0	21	7	75.0%
	SS	0	0	1	7	20	71.4%
	Overall Percent	4.3%	4.3%	7.1%	42.9%	41.4%	71.4%
Testing	STS	0	1	1	0	0	0.0%
	TS	0	0	0	0	0	0.0%
	N	0	0	0	3	1	0.0%
	S	0	0	1	9	3	69.2%
	SS	0	0	0	5	6	54.5%
	Overall Percent	0.0%	3.3%	6.7%	56.7%	33.3%	50.0%

Figure 14. Dimension 8 interactivity variable

Figure 15 below illustrates the combined information presentation of training data, which has a variable interactivity of 66.8%, and test data, which has a variable interactivity of 52.5%.

Overall Percent Correct

Sample	Overall Percent Correct
Training	66.8%
Testing	52.5%

Figure 15. Overall dimensional percentage

IV. CONCLUSION

Based on the results of the analysis carried out using the SPSS application with the neural network method, a relationship was obtained which states that for the first, the data collected in the questionnaire can be used as a data processing operation that produces

100% processed data to make predictions on customer loyalty to retailers via e-commerce applications. Second, dependent factors (px) and supporting factors (cx) influence customer loyalty to use e-commerce applications for the services provided during interactions during online buying and selling transactions, namely 85.4%. The condition for a relationship between variables is good or bad if the R-square value is above 50% which means it is good, if it is below 50% it means it is not good. Third, with a point result of 85.4% in service satisfaction provided during interactions in the e-commerce application, customers are loyal to using the services of the e-commerce application for their next purchase. With satisfactory results for experiments regarding customer loyalty towards e-commerce application providers, this research can be a reference for services in e-commerce applications in Indonesia that increasingly prioritize and pay attention to customer feedback and get closer to customers.

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