Analysis of Product Attributes and Consumers' Satisfaction on Buying Vegetables Using E-commerce Platform During Covid-19

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Abstract. The restrictions on face-to-face activities due to Covid-19 have caused a shift in people's shopping behavior from in-store to online shopping. This condition was also influenced by the rapid development of technology today. Agricultural products, especially vegetables, have also become one of the product groups that have begun to be widely traded online during the Covid-19 pandemic. The purpose of this study is to identify the vegetable attributes considered by consumers and the performance of each attribute on consumer satisfaction through consumer reviews or user-generated content. The method used is descriptive analysis and Naive Bayes. This study uses a purposive sampling method with a total sample of 567 reviews with a rating of 1–3 classified as negative and a rating of 4–5 classified as positive. The results of the study indicate that the overall attributes that are considered and have a positive performance or are considered satisfied by consumers are product attributes, price attributes, and service attributes.

Keywords: e-commerce · user-generated content · Naïve Bayes · consumer satisfaction · commodity

1 Introduction

The Green Economy is a model of sustainable development that takes into account the environmental impact of companies, is growing rapidly, and meeting new customers' requests. Green logistics is one of the aspects involved in that concept, as shipments produce great pollution and have a great impact on the environment. A longer marketing channel means more shipments involved, and also means more pollution released. Whereas, agricultural commodities are products that tend to have a long marketing channel in delivering them from producers (farmers) to consumers. This causes the marketing of agricultural commodities to be very difficult to meet the principles of a green economy. E-commerce can help close this gap since it can shorten the marketing chain in agriculture commodities.

Before the Covid-19 pandemic, the use of e-commerce was not very popular in Indonesian society. However, after the pandemic, things are much different. According to Indonesia's economic records, online trade transactions grew in a positive direction

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during the Covid-19 pandemic, reaching 70 percent throughout 2020 and in 2022, Lazada reported 73% of customers in Southeast Asia see online shopping as a part of their daily life [1].

Consumer behavior has been changing since the Covid-19 pandemic in which online buying, for almost all products, has increased so massively, including agricultural commodities. This behavioral shifting happened as a response to the government policy regarding face-to-face activities restriction during the pandemic. Rapid technological development lately also held an important role in that changing process.

Horticultural commodities, especially vegetables, have become popular commodities that many consumers buy online during the pandemic. The object of this study was focused on tomato buying behavior due to their high risk of delivery. Tomato is one of the daily needs of every Indonesian household [2]. On the other hand, purchasing tomatoes through e-commerce brings high risk as they are easily damaged after being harvested. Problems related to product quality will affect consumer satisfaction. Other factors that can affect customer satisfaction are price and service. To find out the level of consumer satisfaction with tomato, e-commerce platforms provide review features or user-generated content that make it easy for users to share their shopping experiences with other potential consumers. In these reviews, consumers can give a rating on each product purchased, a rating of 1–3 for an unsatisfactory rating and 4–5 for a satisfactory rating. Through these reviews, business actors can also identify what attributes provide satisfaction and dissatisfaction. However, the problem was that the reviews were unstructured texts so further sentiment analysis was needed.

Similar research has been conducted by [3], which examined the sentiment of visitor analysis and compared it in two methods, namely the decision tree algorithm and Naïve Bayes, from this study it was known that the Naïve Bayes had more accurate results in text classification. Other similar studies related to tomato attributes were conducted by [2], and consumer satisfaction research by [4], showed that product, price, and service attributes affect consumer satisfaction. According to these issues and previous research, no one had specifically discussed the analysis of consumer satisfaction through consumer reviews or user-generated content (UGC), so this research tried to fill this gap analysis.

2 Methods

2.1 Collecting Data Method

The data used in this study was secondary data, which includes references through articles, journals, books, websites, and data in the form of user-generated content (UGC) in the form of reviews and ratings written and uploaded by consumers through e-commerce platforms. UGC is a negative or positive statement uploaded by consumers about a product or company and can be seen by others via the internet [5]. These consumer reviews were written in Indonesian as well as reviews that include ratings or assessments with review ratings of 4 and 5 for the positive category or consumer satisfaction and ratings of 1,2,3 for the negative category or consumer dissatisfaction. In addition, the reviews will be used as samples for products that are at the top of the list in the livelihood column related to tomato products and products with the highest number of sales. The number

of samples used in this study was 567 reviews. These reviews are reviews uploaded by consumers in the period 31 July 2021 to 1 January 2022.

Data was collected using web scraping, which is a technique to get information from the website automatically without having to copy it manually [6]. Web scraping focuses on getting data by retrieval and extraction, generally, the data comes from semi-structured documents in the form of web pages in markup topics such as HTML (Hypertext Markup Language) or XHTML (Extensible HyperText Markup Language) [7]. The information that has been obtained then be extracted into a Microsoft Excel format. The document was used as a database to perform data analysis.

2.2 Analysis Method

The data analysis method used in this research was descriptive statistical analysis and the Naïve Bayes method. Descriptive statistical analysis was used to identify the attributes of tomatoes considered by consumers. While the Naïve Bayes method is used to classify negative and positive reviews and to analyse customer satisfaction. In this method, there are several stages as follows.

2.2.1 Pre-processing Data

At this stage, the first step was to change all capital letters to lowercase letters. Next, the review data were grouped into 2 categories, that were positive reviews for ratings 4 and 5 and negative reviews for ratings 1,2, and 3. Then filter the reviews by removing emojis, stopwords, or non-written reviews.

2.2.2 Formulating the Naive Bayes Model

The Naïve Bayes model was formulated using the KH Coder software. The analysis stages were begun with determining the training data and tested the data by dividing them based on ratios, that were 50:50, 66:34, and 80:20, which was then used as a model determinant. The Naïve Bayes equation was described as follows.

$$P(x|C) = P\left(x_1, x_2, x_{3,} \ldots, x_n|C\right) \tag{1}$$

$$P(C) = \frac{N_j}{N} \tag{2}$$

After knowing the results of the two calculations above, the next step was to determine the probability of each class being mentioned using this formula.

$$P(C|x) = \frac{P(x|C).P(C)}{P(x)} \tag{3}$$

where:

P (x|C) = probability of x at certain class
P (C) = probability of certain class
P (C|x) = probability a certain class based on an attribute/a word

P (x) = probability of x
x = data of each attribute (frequency of words mentioned in the review)
C = class (positive or negative comments on the products)
N_j = the number of data from a certain class
N = total number of data

Furthermore, since it used big data, changing the model in log form was needed to avoid significant numerical errors. Then, the model transformed into:

$$\log xy = \log x + \log y \tag{4}$$

$$\log p(x|C).p(C) = \log p(x_1|C) + \log p(x_2|C) + \cdots + \log p(x_n|C) + \log p(C) \tag{5}$$

The log value of $p(x_i|C)$ affected the score that should be added to category C, when the word i appeared once in the document during classification. This meant that if a word appears multiple times in category C in the manual classification example, then documents containing more examples of word i were more likely to be classified into category C as well.

2.2.3 Model Evaluation

The model that has been formed was then tested using data testing. Tests were conducted to determine the level of accuracy, precision and recall. The calculation of accuracy, precision, and recall was described below.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP} + \boldsymbol{TN}}{\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FP} + \boldsymbol{FN}} \boldsymbol{x} 100\% \tag{6}$$

$$Precision = \frac{TP}{TP + TN} x100\% \tag{7}$$

$$Recall = \frac{TP}{TP + FP} x100\% \tag{8}$$

where:

TP = True Positive (true review in positive class/satisfaction)
TN = True Negative (true review in negative class/dissatisfaction)
FP = False Positive (false review in positive class/satisfaction)
FN = False Negative (false review in negative class/dissatisfaction)

These three indicators referred to the confusion matrix according to Table 1.

The results of the evaluation showed how much the model's ability to determine sentiment which includes consumers' satisfaction and dissatisfaction with the tomatoes they purchased on e-commerce platforms. The value of each attribute of tomato would be known based on both classes of consumer satisfaction and dissatisfaction.

2.2.4 Attributes Identification

The results of the comparison of the three ratios of 50:50, 66:34, and 80:20 which showed the highest results were used to classify the overall data and to determine the tendency of attributes in positive or negative classes [8]. Furthermore, the description of the attributes in each class was based on the frequency of occurrence and the probability value.

Table 1. Confusions matrix

		Actual Value	
		Positive	Negative
Predicted Value	Positive	TP	FP
	Negative	FN	TN

Source:[3]

3 Results and Discussion

3.1 Product Attributes that Affect the Consumer's Satisfaction

The review data that has gone through pre-processing was then identified with the emergence of keywords through the KH Coder software. From the identification results, information was obtained about the frequency of occurrence of each word in all reviews. According to [9], when a word often appears in a document, it could be assumed that the word was an important and considered word. Overall product attributes (X_1), price (X_2), and service (X_3) were considered for consumers.

3.1.1 Product

The product attributes that were most mentioned by consumers were the size and weight of tomatoes, which were 469 times, so it could be interpreted that the chili size and weight indicators were the most considered product indicators. Consumers considered the large and small sizes of tomatoes during purchases. These results were reinforced by the research of [10], that the size of tomatoes was one of the consumer preferences during purchase. In reviews, some consumers said that they re-weighed the tomatoes when they arrived to make sure the weight of the tomatoes they received was as ordered or stated in the product description (Table 2).

The next product indicator considered was the quality and condition of the product. Consumers determined the quality based on the condition of the tomato product when it was received and the authenticity of the product (originality). Consumers always demand products that are of good quality, clean and undamaged when they received them because good product quality will provide added value in the minds of consumers, in this case, tomato consumers [4]. Another product indicators considered by consumers were tomato freshness. Freshness means that consumers noticed whether the product was fresh, rotten, or dry. This was in accordance with research conducted by [2] that the freshness and durability of tomatoes were a preference or priority in purchasing tomatoes because consumers consider the safety of the food to be consumed.

The taste and color of tomato were not considered by the consumers too much at the time of purchase, since the frequency of the word "taste" and "color" appeared only 5 times in the overall reviews data, each. These results were in line with the research of [2], which that stated the taste and color of tomatoes were not too prioritized by consumers in purchasing because consumers perceived that those attributes were not too influential when they used tomatoes in their cooking.

Table 2. The frequency of product attributes mentioned in consumer reviews

Variable	Indicator	Keyword	Frequency	Frequency of each indicator	Total frequency
Product (X_1)	Quality ($X_{1.1}$)	Quality	301	385	1.103
		Condition	36		
		Originality	13		
		Watery	20		
		Mushy	15		
	Size and weight ($X_{1.2}$)	Weight	212	469	
		Size	215		
		Big	24		
		Small	18		
	Freshness ($X_{1.3}$)	Fresh	189	239	
		Rotten	46		
		Wilt	4		
	Taste ($X_{1.4}$)	Taste	5	5	
	Color ($X_{1.5}$)	Color	5	5	

Source: Modified data of this research

3.1.2 Price

The price attribute that was most frequently mentioned by consumers was related to catalog prices. Catalog prices are a list of prices offered and listed on the product page. Price lists are needed by online consumers to consider purchases by adjusting the budget and comparing them with other similar sellers [4]. Consumers consider whether the price offered was cheap or expensive. Based on the research results [2], the price was a priority attribute considered by consumers after tomato freshness and durability. On the other hand, discounts and promos were less considered by the consumers when bought tomatoes. The frequency of occurrence of tomato product attributes was briefly presented in Table 3.

3.1.3 Service

The service attribute that was most often mentioned or considered by consumers was delivery (324 times). Moreover, speed and safety of delivery were also considered by online tomato consumers because one of the reasons for consumers to do online shopping was due to its simplicity and time savings used to buy a product [11].

The other service attribute considered by consumers was the seller's response and attitude. Every business actor is required to always provide the best and maximum service for consumers, in online purchases the seller is expected to be responsive and provide a quick response to all consumer complaints and questions. This statement was supported by the results of a study [12], that fast and appropriate seller responses were a consumer

Table 3. The frequency of price attributes mentioned in consumer reviews

Variable	Indicator	Keyword	Frequency	Frequency of each indicator	Total frequency
Price (X_2)	Price on catalog ($X_{2.1}$)	Price	272	331	346
		Cheap	59		
		Expensive	–		
	Discount and promos ($X_{2.2}$)	Discount	5	15	
		Promos	10		

Source: Modified data of this research

Table 4. The frequency of service attributes mentioned in consumer reviews

Variable	Indicator	Keyword	Frequency	Frequency of each indicator	Total frequency
Service (X_3)	Delivery ($X_{3.1}$)	Delivery	171	324	775
		Fast	112		
		Safely	21		
		Courier	20		
	Seller's response and attitude ($X_{3.2}$)	Seller	133	223	
		Quick response	54		
		Friendly	28		
		Service	8		
	Packaging ($X_{3.3}$)	Packaging	83	144	
		Safety	33		
		Neat	28		
	Guarantee ($X_{3.4}$)	Refundable	4	4	
	Colour ($X_{3.5}$)	Suitable	69	80	
		Descriptive	6		

Source: Modified data of this research

priority during online purchases. Moreover, consumers also considered packaging in terms of packaging tidiness and security. Packaging is a concern and important for consumers because of its role in maintaining the freshness and quality of tomato products during distribution [11] (Table 4).

The least considered attribute by consumers, with the fewest frequency, was the refund guarantee and information suitability. According to [13], it was stated that guarantees were an obligation for companies to maintain consumer trust and loyalty. When

Table 5. The results of accuracy, precision, and recall of consumer reviews

	50:50	**66:34**	**80:20**
Accuracy (%)	84,86	88,60	86,84
Precision (%)	90,98	91,62	89,72
Recall (%)	92,06	95,91	96,00
Average (%)	**89,30**	**92,04**	**90,85**

Source: Modified data of this research

consumers get poor service or lack product quality, consumers were entitled to compensation in the form of refunds or exchange of new products. Thus, the suitability of information describes the suitability of the information provided by the seller in the form of a description with that received by the consumer. The suitability of information appeared only 80 times in the reviews and was so much less than other indicators. So, it can be concluded that the suitability of information is not considered.

3.2 Consumer Satisfaction

Based on the data that has been collected, it is known that there are 484 positive reviews and 83 negative reviews. After the review data has gone through pre-processing, then the data were divided into training data and testing data based on a ratio of 50:50, 66:34, and 80:20. Then the training data will be tested into data testing. The test was carried out to determine the level of accuracy, precision, and recall that described the performance of each model that was formed. The Table 5 showed the results of the analysis performed on each model.

Based on the Table 5, it was known that the accuracy or closeness of the actual and predicted values was the highest model with a 66:34 ratio, which was 88,60%, while the highest precision value was a model with a 66:34 ratio, which is 91,62%. Moreover, the highest recall rate was the model with an 80:20 ratio of 96,00%. Overall, the highest average value is the model with a 66:34 ratio of 92,04%. This model then has been used as a model to be tested on the entire data in analysing customer satisfaction. The selection of the model with the highest average was because the model should be able to have results closest to the actual situation. The model with the highest average value was then retested on the overall chili review data of many as 567 reviews which then the results of the analysis were used as a reference in classifying the attributes in each positive and negative category based on the frequency of their occurrence. The Table 6 showed the results of the tomato consumer satisfaction analysis.

Based on the Table 6, it could be concluded that most of the attributes that were considered to have positive performance or have given satisfaction to consumers were the price attribute (X_2) and the service attribute (X_3). Meanwhile, product-related attributes (X_1) as a whole were considered to have negative performance, since three of the five attributes analyzed indicated dissatisfaction of the consumers.

Table 6. The results of the consumer satisfaction analysis

Variable	Indicator	Average probability		Conclusión
		Positive reviews	**Negative reviews**	
Product (X_1)	Quality ($X_{1.1}$)	0,128	**0,138**	Dissatisfaction (negative performance)
	Size and weight ($X_{1.2}$)	**0,212**	0,173	Satisfaction (positive performance)
	Freshness ($X_{1.3}$)	0,133	**0,191**	Dissatisfaction (negative performance)
	Taste ($X_{1.4}$)	0,002	**0,059**	Dissatisfaction (negative performance)
	Color ($X_{1.5}$)	**0,010**	0,000	Satisfaction (positive performance)
Price (X_2)	Price on catalog ($X_{2.1}$)	**0,204**	0,132	Satisfaction (positive performance)
	Discount and promos ($X_{2\cdot2}$)	**0,015**	0,000	Satisfaction (positive performance)
Service (X_3)	Delivery ($X_{3.1}$)	**0,160**	0,018	Satisfaction (positive performance)
	Seller's response and attitude ($X_{3.2}$)	**0,080**	0,005	Satisfaction (positive performance)
	Packaging ($X_{3.3}$)	**0,089**	0,025	Satisfaction (positive performance)
	Refund guarantee ($X_{3.4}$)	0,006	**0,015**	Dissatisfaction (negative performance)
	Information suitability ($X_{3.5}$)	**0,072**	0,022	Satisfaction (positive performance)

Source: Modified data of this research

3.2.1 Product (X_1)

In product, there were five product attributes considered by consumers, there were two indicators that were concluded to give satisfaction to consumers and three other indicators indicated dissatisfaction from tomato consumers. The quality and condition of the product were considered unsatisfactory and had a negative performance according to consumer reviews. Consumers would feel satisfied when the quality provided was as expected. In reviews, consumers commented on how the condition of the product when it was received, consumers were dissatisfied because the product received was in bad condition and some even were watery or mushy. These conditions indicated that there was an excess of water content when they were received by consumers. This was certainly not in accordance with the expectations or expectations of consumers who expect the condition of the product when it arrives in the hands of consumers in the best condition, namely clean, undamaged, and in accordance with what was stated in the product description [4].

Consumers were also dissatisfied with the freshness of the tomatoes, in general. Some consumers said that the tomatoes were not fresh, wilted, and rotten. An example of the reviews *"…these are also a lot of tomatoes that are not fresh"*. Tomatoes are so easily damaged and rotten. So, the sellers need to determine the right strategy in maintaining the quality of the product to keep it good and fresh both in terms of packaging and the selection of delivery services [14]. The taste of tomatoes was also rated negatively by consumers as they were dissatisfied since they got sour tomatoes. These results were in line with [10] and strengthen by [15], which showed that consumers preferred tomatoes with a sweet taste, not sour ones.

The size and weight of tomatoes were considered by consumers as satisfying attributes. In reviews, most of them commented that they were satisfied with the size and weight of the tomatoes they received since it was as expected. In terms of size, consumers felt more satisfied when they got big tomatoes. Meanwhile, in terms of tomato weight, consumers were satisfied if the tomatoes received had the right weight or according to what was ordered or written in the product catalog. The results also indicated that the attribute of color also gave satisfaction to consumers but was not too considered by the consumers. According to the reviews, it proved that consumers were satisfied with tomatoes that have bright, beautiful, and good color. This was supported by the results of research [15], which proved that consumers like tomatoes with bright red color and an external appearance without any spots or wounds.

3.2.2 Price (X_2)

The attribute of catalog prices has a higher probability value on positive reviews than negative reviews. In other words, it means that consumers tend to be satisfied with the prices offered. Based on analyzed reviews, consumers were satisfied with the prices offered by sellers since the prices were affordable for them. These results were supported by the research results of [5], which stated that consumers felt unwilling to pay for products when their prices did not suitable to their quality. Otherwise, when compared to catalog price, the attribute of "discounts and promos" had less frequency of occurrence

but it still had an impact on consumer satisfaction. For example, giving cash back, a kind of promo, would increase the satisfaction of the buyers.

3.2.3 Service (X_3)

Delivery was analyzed as one of the attributes of the service dimension, and was rated as a quite satisfactory variable by consumers. This conclusion came up as the probability value of its occurrence was higher in positive reviews than in negative ones. According to the reviews, most of the consumers were satisfied with the on-time and safe delivery service. This result was similar to [16], which also proved that the speed and accuracy of delivery affect consumer satisfaction. This was also supported by the research results of [12], which showed that delivery duration had a significant effect on consumer satisfaction.

Furthermore, the sellers' responses and attitudes also evidently gave an impact on increasing positive reviews for the products. Most of the consumers agreed delivery time on online purchased-commodity was quick enough. They were also satisfied with the responsive sellers since they answered their chat fast. Related to this matter. Research conducted by [17], also showed that responsiveness has a positive effect on consumer satisfaction. Packaging, as one of service attribute, was considered satisfactory by consumers and had a positive or good performance. Consumers were impressed by the neat and safe packaging used on tomatoes during delivery.

The results of the consumer satisfaction analysis indicated that the indicator of the guarantee tend to get negative reviews from the consumer that the positive one. It could be seen from its probability of appearing in the negative reviews was greater than its positive reviews. So, it could be concluded that the consumers of tomatoes, felt dissatisfied with the performance of the "guarantee" variable during their online purchasing of tomatoes. While the suitability information provided by the seller, especially about product description and images, was proven to affect consumer satisfaction regarding the high probability of a positive review appearance. It means that consumers will be satisfied when the product received is in accordance with the information provided by the seller on their account on the e-commerce platform.

4 Conclusion and Implication

Overall, the attributes that were considered to have had a positive performance in providing satisfaction to the consumers were the price (X_2) and the service (X_3) attributes. Meanwhile, product attributes (X_1) were also considered by the consumers, but those attributes had a higher probability to have a negative performance on consumer satisfaction, according to the consumer reviews. In detail, the tomato attributes that were considered the most by the consumers and tend to have positive performance were: 1) size and weight, 2) catalog prices, 3) quick response, 4) delivery time, and 5) packaging. Meanwhile, attributes of quality and condition and freshness of tomatoes were considered to have negative performance. Moreover, the analysis results showed that attributes of color, discounts and promos, as well as information suitability, were less considered by the consumer, but had a positive performance in increasing consumer satisfaction.

Last, the indicators of taste and guarantee (refund) were not considered and also gave a negative performance to customer satisfaction. According to Naïve Bayes model testing, the results indicated that the best performance model for predicting consumer satisfaction was used the 66:34 ratio, with the average value of accuracy, precision, and recall value was 92,04%.

Regarding the conclusions of the study, suggestions that can be given for vegetable sellers, especially tomato sellers, on any e-commerce platforms, are that they expected to focus on attributes that are more considered by consumers but still showed a negative performance on consumer satisfaction, the freshness in particular. Sellers or business actors should pay more attention to maintaining the freshness of their vegetables during the distribution process until they were received by consumers. One of the strategies to overcome this problem is by choosing or using suitable and safer packaging. The packaging should give maximum protection, has good air circulation so that the vegetables do not get watery. Some of the recommended packaging materials are bamboos, clear polyethylene, or mesh bags. In addition, post-harvest handling process also need to be prioritized, such as sorting the best item to sell, or drying of wet vegetables before being packaged. Further research should analyze more data and more commodities as research objects, so word detection can be more accurate. Further research should seek for more selection features on pre-processing data before being analyzed with Naïve Bayes to improve classification performance.

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