Does it Pay to be Perfect? A Lesson Learnt from CV XYZ

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Abstract

E-commerce provides an excellent opportunity to increase the company revenues, especially during the COVID-19. Many features that appear in the E-commerce platform can influence the customer purchase intention. Therefore, most companies strive to achieve the highest maximum Star-rating that serves as the electronic version of word of mouth. CV XYZ expects to increase the 5-Star-rating count by creating the after-sales service program. However, does it pay to be perfect? By collecting Star-rating data from six online stores across three different online marketplaces organized by CV XYZ, we develop simple Statistics to a more sophisticated Markov Chain and Regression to analyze the data. The result shows that the distribution movement of Star rating before and after implement the program is not significantly different. However, the after-sales service program greatly improved the average daily Sales around IDR 31M (p-value for the T-test = 0.0039). By simply using Pearson Correlation analysis, we found a negative correlation between Sales and Star-Rating counts that encounter us in the "too good to be true" phenomenon. Therefore, it is more critical for the company to figure out an optimal number of 5-Star ratings achieved to maximize Sales than only focus to achieve the highest 5-Star ratings.

Keywords
After-sales service, Star-rating, Sales, Statistics and Markov Chain.

1. Introduction (12 font)

E-commerce is becoming one of the essential tools that people need during this digital era. It offers a new medium where people could do transactions through the internet and online platforms (Syazali et al., 2019). The number of e-commerce users keeps increasing, especially during this COVID-19 pandemic situation, where people need to limit social activities. Due to this limitation, online shopping becomes one of the media for consumers to satisfy their needs (Koch et al., 2020). Based on the data retrieved from katadata.com, more than 200 million people in Indonesia visit different online marketplaces during the third quarter of 2020, as shown in Figure 1. With more than 200 million visitors with different satisfaction standards, it is needed for a company or firm to have a specific evaluation of their available services. Without a good service standard, it would be challenging to maintain customer loyalty and satisfaction (Sivadas & Baker-Prewitt, 2000). Dhiranty et al. (2017) studied customer trust in Tokopedia and found out that customer trust could influence their purchase intention. For example, low ratings mean less trust for the potential customer, reducing the intention to purchase.

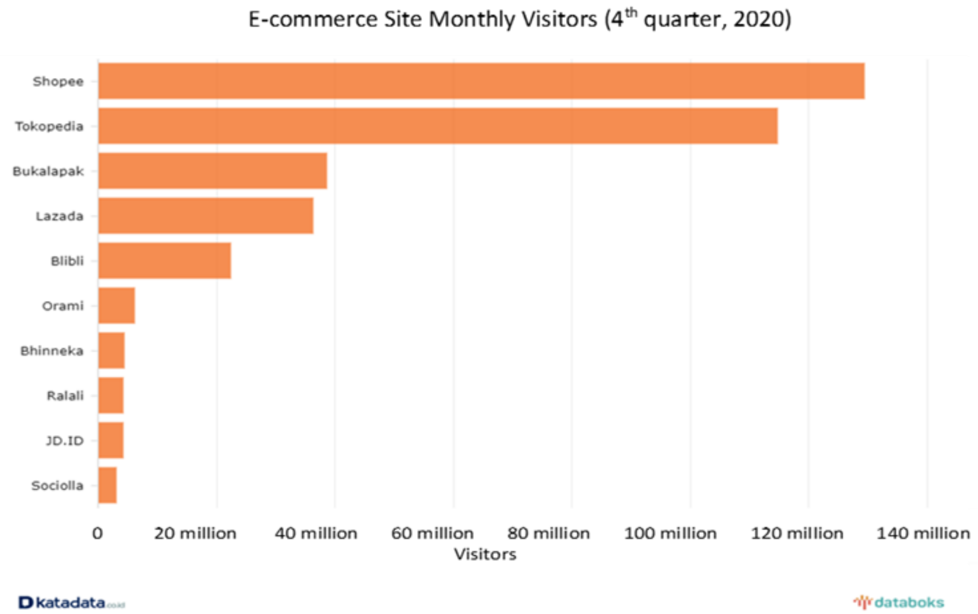

Figure 1. Top 10 e-Commerce with highest visitor during Q3 2020 (https://databoks.katadata.co.id/)

In this research, we proposed a case study from a sole proprietorship (company) that imports Point of Sales (POS) Machines, call CV EYZ. POS Machine consists of Thermal Printer, Barcode Printer, Barcode Scanner, Cash Register, and accessories. The company sells its product via offline and online selling. The company started its business in 2010 when it started to offer screen protectors for phones and sold them across Indonesia. The company acquired many customers and became one of the biggest points of sales suppliers in Indonesia. In 2019, the owner tried to expand their business through the online marketplace. They tried various methods and still unable to increase the revenue gained from each marketplace. The owner saw some potential in online markets, especially during this pandemic season. COVID-19 Pandemic situation forces people to work from home, search for other jobs, or become online sellers. The products that CV XYZ sells are suitable for people who need their home business, small shops, or maybe small retail businesses. CV XYZ has 6 stores on 3 different online marketplaces (Shopee, Lazada, and Tokopedia).

The owner believed that after-sales service is one of the critical predictors, among other factors that influence customer satisfaction (Kurata & Nam, 2010). Furthermore, after-sales services can also be categorized as Service Quality, where the company will give a particular service to their buyers. Delivering a successful service can give a competitive advantage over other firms (Murali & Muralidharan, 2016). Therefore, the owner believe that it is important for CV XYZ to maintain a good service quality for improving customer satisfaction level.

This paper shares our lesson from a sole proprietorship in Indonesia that sells point of sales (POS) products on several online marketplaces to drive customer satisfaction higher through after-sales services. In the next section, we provided a literature review of this subject. Next, we outline an effort that an owner is setting to achieve 4- and 5-Stars rating as the theoretical foundation that supports his idea. We then develop several methodologies ranging from simple Statistics to a more sophisticated Markov Chain and Regression that we can use to measure his effort. Finally, based on our findings, we provide our discussions and recommendation for the business and further research.

1.1 Objectives (11 font)

This paper aims to evaluate whether the effort and resources that are spent already in the after-sales service result in the positive movement for the Star rating from 3-Star (and lower) to 4-Star (and higher) and improve the Sales of online stores.

2. Literature Review

Star-rating (on a 5-point scale) has been the subject of debate for many years. For example, Breinlinger et al. (2019) argued that while simple five-star ratings for the online marketplace are good enough at identifying and weeding out very low-quality products or suppliers, they do a poor job of separating good from great products or suppliers. They also provided several suggestions to remedy the situation. Klein et al. (2018) pointed out that reviews are heavily polarized with many extreme positive and negative. Thus, it has a dual-edge sword challenge to consumers. It could be a blessing to help other customers making an informed decision, but it usually represents the most extreme views. They suggested using both monetary and pro-social incentives to remedy these extremes and have a more balanced review.

Similarly, in 2010, Williams et al. released their sophisticated 5-Star scoring system developed using Statistics methodology for Centers for Medicare and Medicaid Services (CMMS) to rate nursing homes. Please be clear that CMMS, in this case, is a United States government agency that serves older people. However, in 2015, Konetzka et al. published a paper with criticism over that those 5-Star system. The debate on this subject continues until very recently, with CMMS planning to release its updated version.

Despite all of those debates, Askalidis and Malthouse (2016) can demonstrate that the number of reviews for a particular product serves as the electronic version of word of mouth commonly encountered in the marketing diffusion process. Using data from a specialty retailer, they demonstrated that the number of reviews could increase conversion rate as much as 270%. The function that they use to fit the data is the famous exponential learning curve. Furthermore, Maslowska et al. (2017) are also able to demonstrate there is a non-linear relationship between probability to purchase (as dependent variable) vs. average Star-Rating reviews (valence) and volume of reviews as independent variables using logistic regression with generalized additive models.

The above two research by Askalidis & Malthouse (2016) and Maslowks et al. (2017) inspire our 3rd hypothesis (see below). However, we did not have the luxury to have similar data since online marketplaces host our online stores.
In addition to the above debate, Luca and Zerva (2015) provide a completely different perspective when analyzing Yelp reviews. Even though, not directly related to our research, the interesting finding in their research is related to the fake negative review due to competition. They pointed out that competition can indeed increase the number of the negative review.

3. Methods

Given the obsession of the owner with the 5-Star rating, the relatively short duration of the after-sales service program, and the available data from the online marketplaces that we can collect, we collected the Star rating of CV XYZ online stores and compared them before and after. We formulated the following three hypotheses:

H1: Given the effort and resources spent already in the after-sales service, there should be some positive movement in the Star-rating, from 3-Star (and lower) to 4-Star (and higher).
H2: The after-sales services will help to improve the Sales of online stores.
H3: There is a positive correlation between Sales and Star-Rating counts.

For the 1st hypothesis, we collected the data from Shopee Axelpos (https://shopee.co.id/axelpos) and 5 other online stores that CV XYZ owns across 3 different online marketplaces. In this paper, we only use the Star rating data from Shopee Axelpos to illustrate our findings. Other online stores exhibit similar behavior. It is also important to point out that this Star rating system is for each product. However, we use them collectively as proxy data for the “after-sales service” program implemented since the program was implemented for all products. For the “before” after-sales service program, we believe we can take a simple average for the proportion since the program has been like that for an extended period, i.e., reach steady-state. We also compare the number to the Markov-Chain steady-state to validate our assumptions. However, given the short history of the data “after” the after-sales service program was implemented, we think it is more appropriate to model the Star rating as a Markov Chain. So, our first task is to estimate the transition probability and then calculate the stationary probability to see how the process behaves for the long run when it reaches a steady-state probability.

A Discrete-Time Markov Chain (DTMC) is a sequence of random variables with transition probability matrix P that represents probability from one state to the other; our 5-Star rating data very much resembles the DTMC, that is:

$$Pr(X_{n+1} = x_{n+1} | X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) = \Pr(X_{n+1} = x_{n+1} | X_n = x_n) \tag{1}$$

In our case, the state space $S = \{s_3, s_4, s_5\}$ is the Star-rating where: s_3 = 3–Star (or less), s_4 = 4–Star, and s_5 = 5-Star respectively. This chain moves from one state to another, and the transition probability to move from s_i to s_j is given by p_{ij}. In this case, we assume that our after-sales services have an underlying time-homogeneous Markov Chain such as in (2) below:

$$\mathbf{P} = \begin{bmatrix} p_{33} & p_{34} & p_{35} \\ p_{43} & p_{44} & p_{45} \\ p_{53} & p_{54} & p_{55} \end{bmatrix} \tag{2}$$

In its simplest form, following Dent & Ballintine (1971), an unconstrained least square estimate for the transition probability is given by the following matrix multiplication (first proposed by Miller (1952) and subsequent correction from Goodman (1953):

$$\mathbf{P} = \mathbf{N}\mathbf{M}^{\mathrm{T}}(\mathbf{M}\mathbf{M}^{\mathrm{T}})^{-1} \tag{3}$$

where **M** is the matrix of observed proportions for observations 1 to $n - 1$ (n is the total number of observations or time periods), and **N** is the matrix of observed proportions 1 observation beyond M (*i.e.*, observations 2 through n).

Unfortunately, it is well known that the unconstrained least square estimate can produce negative probability and probability bigger than one. Numerous research papers (Madansky (1959), Telser (1963)) had been published to illustrate the challenge, as well as some proposed corrections in estimating the transition probability from aggregate data. One of the most highly cited topics in this topic is the book created by Lee et al. (1970) that proposed a quadratic programming formulation. There are also several other techniques as discussed in Dent & Ballintine (1971) to get a reasonable estimate. Unfortunately, each of them has its challenges. We tried to use it and encountered this problem when we applied some of this technique to the Star-Rating data that we have collected from CV XYZ. We obtained some result that does not make too much sense (unconstrained least-square produce negative and beyond unity probabilities, etc.).

Another way to fit the Markov Chain transition probability is by observing its sequence of events. There are 4 commonly used methods as outlined in Spedicato & Simorelli (2013), Spedicato et al. (2017): maximum likelihood, maximum likelihood with Laplace Smoothing, Bootstrap approach, and maximum a posteriori. We successfully used these techniques together with a traditional averaging observation to see if we could extract some useful information. The maximum likelihood of the transition probability p_{ij} (and also with Laplace smoothing α), its standard error SE_{ij}, and Confidence Interval are given by the equations (4.a), (4.b), (5), and (6) below:

$$\hat{p}_{ij}^{MLE} = \frac{n_{ij}}{\sum_{u=1}^{k} n_{iu}} \tag{4.a}$$

$$\hat{p}_{ij}^{LS} = \frac{(n_{ij}+\alpha)}{\sum_{u=1}^{k}(n_{iu}+\alpha)} \tag{4.b}$$

$$SE_{ij} = \frac{\hat{p}_{ij}^{MLE}}{\sqrt{n_{ij}}} \text{ or } SE_{ij} = \frac{\hat{p}_{ij}^{LS}}{\sqrt{n_{ij}}} \tag{5}$$

$$[LB, UB] = \left[\hat{p}_{ij}^{MLE} - zscore(CL) \times \frac{\hat{p}_{ij}^{MLE}}{\sqrt{n_{ij}}}, \hat{p}_{ij}^{MLE} + zscore(CL) \times \frac{\hat{p}_{ij}^{MLE}}{\sqrt{n_{ij}}}\right] \tag{6}$$

In addition to the Star-Rating data, we also obtain the Sales data from 6 online stores that CV XYZ owns. For the 2nd hypothesis (H2), we compare the average daily sales before and after-sales service program is implemented to see whether it has a positive impact by using a very simple two-sample t-test with unequal variance. As we have discussed in the literature review, the 3rd hypothesis (H3) is inspired by the work of Askalidis and Malthouse (2016) as well as Maslowska et al. (2017). However, given that our data is at the aggregate level (not collected at the individual product level), we try to see the correlation between average daily Sales and Star Rating counts both on linear and exponential functions. In the next section, we discuss our findings in more detail using Shopee Axelpos online store data.

4. Data Collection

The characteristics of data that we can collect are as follows:

- For the "before" (Prior) situation, it is about 1 month (March 14 – April 17, 2021) of daily data before the after-sales service program is implemented. There are 1369 data points during this period since several star ratings were posted daily.
- Similarly, the "after" (Post) situation also consists of about 1 month (May 16 – June 19, 2021) of daily data post the after-sales service program, and we can collect 1768 data points of Star Rating.

5. Results and Discussion

5.1 Analysis of H1

The basic statistics of our Star-Rating data looks like the following Table 1 (please note that we combine 1-Star and 2-Star into 3-Star since their counts are very marginal):

Table 1. The proportion star-rating relative to the "after-sales service" program

	≤ 3-Star	4-Star	5-Star
Before	21	124	1224
After	25	151	1592

	≤ 3-Star	4-Star	5-Star
Before	0.0153	0.0906	0.8941
After	0.0141	0.0854	0.9005

Notice that even though the proportion looks slightly better post the after-sales service program was implemented, the *p*-value of $\chi2$ (= 0.8412) reveals that the distribution of Star rating for Before and After data are not very significant. Not quite satisfy with the above result, we use the Markov-chain package from Spedicato *et al.* (2017) that is available in R to estimate the transition probability and were able to obtain the following results in the Table 2.a., 2.b., and 3 for the transition probability matrix as well as its corresponding standard error:

Table 2. Transition probability and their corresponding SE before program implementation

p Before	≤ 3-Star	4-Star	5-Star
≤ 3-Star	0.04762	0.14286	0.80952
4-Star	0.01613	0.17742	0.80645
5-Star	0.01472	0.08095	0.90433

SE Before	≤ 3-Star	4-Star	5-Star
≤ 3-Star	0.04762	0.08248	0.19634
4-Star	0.01140	0.03783	0.08065
5-Star	0.00347	0.00814	0.02719

Table 3. Transition probability and their corresponding SE after program implementation

p After	≤ 3-Star	4-Star	5-Star
≤ 3-Star	0.129032	0.129032	0.741936
4-Star	0.021429	0.214286	0.764286
5-Star	0.015047	0.066458	0.918495

SE Before	≤ 3-Star	4-Star	5-Star
≤ 3-Star	0.06452	0.06452	0.15470
4-Star	0.01237	0.03912	0.07389
5-Star	0.00307	0.00645	0.02400

Table 4. Steady-state probability before vs. after system implementation

Rating	≤ 3-Star	4-Star	5-Star
ss Prob Before	0.015351	0.090643	0.894006

Rating	≤ 3-Star	4-Star	5-Star
ss Prob After	0.017554	0.079275	0.903171

Unfortunately, applying equation (6) to Tables 2 and 3, we can easily see no difference in terms of the Star Rating transition probability. Similarly, the *p*-value of $\chi2$ for the steady-state probability gives us 0.9995, which means the steady-state probabilities Before and After the after-sales service program are practically identical.

Hence, we have to conclude that there is insufficient evidence to reject the hypothesis that we obtain a higher Star rating due to the after-sales service program. The possible reason for this condition is that the implementation of this program is evaluated in 1 monthly data only; the program benefit is gained more internally for the company in tracking the progress of after-sales service so than to the customer. Anyway, before the program is implemented, the company already provided the after-sales service to the customer.

5.2 Analysis of H2

The very fundamental analysis on the sales is that we are comparing the average daily sales for the prior after-sales service program is implemented vs. post-after-sales service program. Therefore, our data for Shopee Axelpos is presented in the following Table 5 (other online marketplaces exhibit similar behavior, just at different scales):

Table 5. Average daily & St dev daily sales for prior *vs.* post after-sales service for Shopee Axelpos

	Average Sales/Day	**StDev Sales/Day**
Before	IDR 23,741,462.07	IDR 9,358,087.17
After	IDR 35,341,617.31	IDR 16,121,089.60

The *p*-value for the *T*-test is 0.0013. It clearly indicates that the daily Sales post-implementation of the after-sales service program has a great improvement, even though its standard deviation (and variance) is slightly higher. Based on the data so far, we can safely conclude that the investment in the after-sales service program produced an increase in average daily Sales for over IDR 11M. Combining the Sales of all 6 online stores, CV XYZ can see an increase on average daily Sales of around IDR 31M after implementing the after-sales service (with a *p*-value for the *T*-test = 0.0039) – a big clear payoff for the investment in the after-care service program. Table 6 summarizes the average daily sales and standard deviation for all 6 online stores combined.

Table 6. Average daily & St Dev daily Sales for prior *vs.* post after-sales service for all 6 online stores

	Average Sales/Day	**StDev Sales/Day**
Total Before	IDR 89,815,701.38	IDR 30,344,817.70
Total After	IDR 121,393,370.77	IDR 49,946,415.02

5.3 Analysis of H3

Hypotheses 3 is the area that we originally were skeptical about the finding in Maslowska et al. (2017). When we formulated our 3rd hypothesis, we thought there should be a positive correlation between the Sales and the numbers of 5-Star ratings – hence, our stated hypothesis above. We feel the owner of CV XYZ expectation is very reasonable, i.e., to expect and try to increase the number of 5-Star-rating continuously. Therefore, we calculate Pearson's correlation between sales and the log of the counts for 5-Star (as well as 4-Star and 5-Star ratings) before and after-sales service program implementation. To our (originally) surprise, we got the result shown in Table 7. The following table displays those results (again, the table below is only for Shopee Axelpos – other online stores exhibit similar behavior at a different scale).

Table 7. Correlation between Sales and Star-Rating counts (in logarithmic scale)

	ρ(Sales, Ln(5-Star))	**ρ(Sales, Ln(4- or 5-Star))**
Before	-0.3122	-0.3219
After	-0.8209	-0.8120

We use a logarithmic scale for the counts of Star rating for the same reason as Maslowska et al. (2017), i.e., to make data a bit normal (normalize skew data with outliers). From Table 7, we see there is a negative correlation between Sales and Star-rating counts. We are now convinced that too many 5-Star ratings could actually bring Sales down as the old saying: "When it is too good to be true, it probably is." Our finding indicates that it is possible, and the owner of CV XYZ needs to be very careful when driving the 5-Star rating up.

After our finding above, we also went back to conduct a literature review and found an interesting Mathematical explanation of this (now) famous advertising/marketing phenomenon of "too good to be true", this time in various subjects. One of such paper is by Chapeau-Blondeau et.al. (2016). Moreover, it also turns out that several other researchers in a completely different subject, such as Baier et al. (2021), have discussed a similar topic.

6. Conclusion (12 font)

From the above simple case study, it is very clear that we encountered what has been alerted by Klen et al. (2018) and Breinlinger et al. (2019) regarding Star Rating. Our data also shows that we have an extreme rating (user can compare the counts for ≤ 3-Star vs. 5-Star and notice that the counts skew heavily toward 5-Star). Unfortunately, those 4-Star and 5-Star ratings do not provide us with any further inside in terms of their counts. We failed to prove our 1st hypothesis (H1) by just looking into the number counts. Furthermore, we also encounter the "too good to be true" phenomenon between Sales data with those 5-Star ratings in particular (as in H3).

Obviously, the failure to prove our 1st and 3rd hypotheses suggest that we need to dig deeper into those 4-Star and 5-Star rating as had been suggested previously. For example, suppose CV XYZ wants to get a more realistic understanding of its customers. In that case, we recommend providing a monetary incentive (e.g., in terms of coupons for further purchase, etc.) for those reviewers so that they can provide more elaborate reviews. Otherwise, that 5-Star (and also 4-Star) rating serves as decorations. Obviously, we have investigated those 1 – 3 Star ratings (since there are only a few of them and concluded that there is no fraud due to competition or other factors.

Similarly, under the assumption of the "too good to be true" phenomenon, it will be exciting to figure out whether there is an optimal number of 5-Star ratings that certain companies will need to achieve in order to maximize Sales. Of course, assuming that actual data can be collected, it is also interesting to see how the length of honest reviews correlates to the Sales of a particular product or general sales for an online store.

Lastly, while at first glance it does not seem that the amount of investment in the after-sales service produces the 5-Star rating that the owner wanted, the Sales data demonstrated that the after-sales services program indeed increased the average daily Sales substantially significantly (Statistically significant). Hence, it proves our 2nd hypothesis (H2) and motivates CV XYZ employees to improve further and measure the after-sales service program. At the same time, it should be clear that CV XYZ will need to be very careful with the number of 5-Star ratings so that it does not negatively affect the Sales as the "too good to be true" phenomenon seems to apply here.

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