Global Scientific and Academic Research Journal of Economics, Business and Management
ISSN: 2583-5645 (Online)
Frequency: Monthly
Published By GSAR Publishers
Journal Homepage Link- https://gsarpublishers.com/journals-gsarjebm-home/

MULTICRITERIA METHODS ANALYSIS AND CONSUMER SATISFACTIONSCORE: A CONSENSUS ANALYSIS ON BRAZILIAN E-COMMERCE

BY

Adhmir Renan Voltolini Gomes[1], Prof. Dr. Nelson Hein[2]

[1]Ph.D. Candidate in accounting and management from the Department of Postgraduate in Accounting at Blumenau University.
[2] Professor at the Department of Postgraduate in Accounting at Blumenau University.

Article History

Received: 05/01/2024
Accepted: 10/01/2024
Published: 11/01/2024

Vol – 3 Issue – 1

PP: -21-28

Abstract

This paper aimed to analyze the odds ratio between the results obtained by the multicriteria methods (Adriana, DP2, and EDAS) and the consensus of the consumer review score in e-commerce. This study was conducted through archival research and is characterized as experimental. The data refers to the Brazilian E-Commerce Public Dataset available by Olist Store at the online community of data scientists and machine learners – Kaggle. The database contains records of the year 2016 to 2018 made at multiple marketplaces in Brazil. For data analysis, we used a machine learning technique and logistic regression models. Logisticregression makes it possible to analyze the odds ratio of the occurrence of an event about the consumer review. Both the multi-criteria methods (Adriana, DP2, and EDAS) and the consensus analysis of the responses can allow insights into the financial information of companies. Therefore, these results highlight the importance of analyzing the consensus of consumer reviews in addition to the managerial processes that can contribute even more to improving the processes involved. The results observe the relevance of not breaking consumer confidence regarding the time processes estimated, as this fact directly impacts the review score. The consensus analysis presented that, in addition to seeking a high average in consumerreviews, managers must observe the consensus on reviews, so that inconsistencies can be reviewed.

Keywords: Multicriteria methods; Consumer satisfaction; Consensus analyses, E-commerce.

1 INTRODUCTION

An increasingly popular alternative among consumers and sellers, facilitated by technological advancements, is e-commerce. This surge in popularity is primarily attributed to the seamless interaction it offers between users (Bhaskar & Kumar, 2016). It is noteworthy that technology now pervades various aspects of people's daily lives, instilling confidence in users who engage in e-commerce transactions (Rajendran, Wahab, Ling & Yun, 2018). This adoption is fueled by the virtual environment's capacity to overcome traditional constraints such as time and space, as highlighted by Bhaskar and Kumar (2016).

Moreover, Sameti, Khalili, and Sheybani (2016) posit that individuals' embrace of e-commerce transactions can significantly contribute to the economic growth of developed countries. The expansive reach of e-commerce, as evidenced by Vasić, Kilibarda, and Kaurin (2019), has exhibited notable growth in competitiveness over the last decade when compared to traditional commerce. Initially met with resistance from consumers, particularly concerning the security of online transactions, the evolution of e-commerce experiences has played a pivotal role in dispelling these security concerns (Vasić, Kilibarda & Kaurin, 2019).

Partly, the establishment of this trusting relationship is attributable to the evolution ofe-commerce platforms and the accessibility of information about advertisers (Vasić, Kilibarda & Kaurin, 2019). Consequently, consumer evaluations emerge as a pivotal factor for advertisers, influencing potential buyers' decisions to engage in transactions (Wijayajaya & Astuti, 2018; Delima, Ashary & Usman, 2019; Vasić, Kilibarda & Kaurin, 2019). These evaluations play a dual role, impacting not only the initial decision to proceed with negotiationbut also influencing subsequent decisions, such as the choice to repurchase from the same seller and the drive to enhance market competitiveness

*Corresponding Author: **Adhmir Renan Voltolini Gomes.**

(Darko, Terkper, Novixoxo, & Anning, 2018).

The global reach of e-commerce shatters traditional geographic constraints, making it an indispensable option for sellers. Consequently, the absence of an e-commerce presence could lead to a loss of market competitiveness, given its ability to transcend city, state, and national boundaries. Recognizing this, Hikmah and Afridola (2018) note that consistently maximizing consumer satisfaction poses an ongoing challenge for companies striving to secure consumer trust.

In that perspective, Kumar (2016), Di Fatta, Musotto and Vesperi (2016), Sameti, Khalili, and Sheybani (2016), Rajendran, Wahab, Ling, and Yun (2018), and Vasić, Kilibarda and Kaurin (2019) comment that the order from purchase to delivery to customers are steps that need to be constantly under analysis by managers, as it can influence consumer satisfaction.

Based on these processes, the objective of this research is to analyze the odds ratio between the results obtained by the multicriteria methods (Adriana, DP2, and EDAS) and the consensus of the consumer review score in Brazilian e-commerce. According to IBGE (2019),Brazil has a population of over 210 million people, making that country a potential consumer market. For this, the question that guides the research is what is the odds ratio between the purchase order processes to the delivery of the products and the consensus of consumer reviewsin e-commerce?

To answer that question, we structured the research development into five sections. The first section is the introduction. In the second section, we highlight the theoretical framework. In the third section, we detail the methodological procedures. In the fourth section, we discuss the results. Finally, in the last section, we present the final considerations.

2 THEORETICAL FOUNDATION

2.1 Costumers Satisfaction and Lead Time

Consumer satisfaction holds significant importance for both company managers and researchers in the business domain. Consequently, numerous studies have delved into the analysis of consumer satisfaction, aiming to comprehend the various factors shaping this critical aspect. For instance, Hikmah and Afridola (2018) conducted a comparative study on consumer satisfaction in online and offline markets, unveiling distinct differences and relationships within these realms. They emphasized variations in interpersonal communication indicators such as openness, empathy, support, positivity, and equality.

Thus, consumer satisfaction, a multifaceted concept, is influenced by various factors. Arinda, Soetjipto, and Hermawan (2018) point out that product quality, brand image, and menu variety can significantly impact satisfaction and, consequently, consumer loyalty. Similarly, Sari and Giantari (2020) highlighted the role of product quality in influencing satisfaction and fostering repeat purchases. Furthermore, Delima, Ashary, & Usman (2019) observed that service quality, product quality, price, promotion, and brand image collectively contribute to positive and substantial effects on consumer satisfaction and loyalty.

In the online market, consumer loyalty manifests in the intention to repurchase products and services (Wijayajaya & Astuti, 2018). The quality of electronic service emerges as a pivotal factor influencing consumer satisfaction, thereby linking to the company's trust and reputation—elements that positively shape consumers' intentions to repurchase (Wijayajaya &Astuti, 2018).

In the online market, consumers navigate various aspects, given the virtual nature of interactions. Within this environment, multiple steps, spanning from the initiation of a purchase order to the delivery of products, can significantly influence consumer satisfaction. Accordingto Darko, Terkper, Novixoxo, and Anning (2018), one crucial aspect is minimizing the waiting time for products, as this directly correlates with heightened consumer satisfaction. Successfully managing to reduce delivery times or meeting the stipulated timeframe is perceived as a positive factor contributing to consumer satisfaction.

Online markets present distinct characteristics and operational complexities compared to traditional in-store purchases. Mohamed and Coutry (2015) underscore the pivotal role of delivery time in shaping consumer satisfaction within the online purchase process. In their analysis encompassing the stages of purchase order, order fulfillment, and product delivery, Mohamed and Coutry (2015) revealed that 30% of products were delivered after the estimateddate. Significantly, they highlighted that the type of product, logistic parameters, order size, andcustomer type exert substantial impacts on lead time.

Within the online market, consumers engage with various facets, given that interactions occur within a virtual environment. Numerous steps, ranging from the initiation of a purchase order to the delivery of products, hold the potential to influence consumer satisfaction in this digital realm. Darko, Terkper, Novixoxo, and Anning (2018) assert that the reduction of waitingtime for products is pivotal for enhancing consumer satisfaction. From this perspective, a company's ability to minimize delivery times or meet established timelines is perceived as a positive factor contributing to consumer satisfaction.

Online markets exhibit distinct characteristics and operational complexities in comparison to traditional in-store purchases. Mohamed and Coutry (2015) contend that a fundamental factor shaping consumer satisfaction in the online market purchase process is delivery time. Through an analysis encompassing the stages of purchase order, order fulfillment, and product delivery, Mohamed and Coutry (2015) uncovered that 30% of products were delivered after the estimated date. Based on this analysis, they highlighted the substantialimpact of component type, logistic parameters, order size, and customer type on lead time.

2.2 Previous Studies

*Corresponding Author: **Adhmir Renan Voltolini Gomes.**

The prevalence of e-commerce transactions continues to surge among consumers. However, according to Vasić, Kilibarda, and Kaurin (2019), a unanimous shift among consumers has not occurred, as there remains a segment that favors the traditional purchasing model. These individuals opt for the experience of visiting department stores to inspect and purchase products. Consequently, sellers face the challenge of devising compelling alternativesto entice these consumers into establishing a meaningful relationship with e-commerce platforms (Vasić, Kilibarda, & Kaurin, 2019). As a result, customer satisfaction emerges as a complex construct influenced by myriad factors, encompassing security, information availability, shipping, product quality, and pricing. Notably, factors such as shipping costs play a significant role in predicting customer satisfaction (Vasić, Kilibarda, & Kaurin, 2019).

In the context of India, Bhaskar and Kumar (2016) assert that, for e-commerce sellers, the crux lies in maintaining customer satisfaction, with delivery punctuality and accuracy at the requested location being crucial determinants. Thus, e-commerce sellers wield the power to shape consumer confidence. The intricate relationships among factors reveal a structured dynamic — trust influences interactivity, and both trust and satisfaction collectively impact customer loyalty. However, it is essential to acknowledge the study's limitations, particularly in terms of its sample size. Despite encompassing diverse age groups and genders, the results may not be universally applicable. Nevertheless, the implications drawn from these findings offer insights into relationships that can be extrapolated globally, extending beyond the context of India.

Taking a focused approach to discern the determinants of quality issues on WEB, Di Fatta, Musotto, and Vesperi (2016) systematically categorized factors using a Pareto chart. Their findings highlighted those eight resources significantly influenced the studied quality. The distinctive advantage of their methodology lies in the establishment of a preferential order. Notably, the results underscore that emotional characteristics supersede technical aspects in terms of relevance. Applying the Pareto principle, the study revealed that discount offers, free shipping, and ease of use play decisive roles in shaping quality perception (UPWQ). Di Fatta, Musotto, and Vesperi (2016) advocate for a managerial focus on developing these three aspectsbased on the identified critical factors.

Shifting the focus to user and customer motivational factors on commercial websites, Sameti, Khalili, and Sheybani (2016) conducted a comprehensive analysis. Employing a combination of a questionnaire and the Delphi method, they performed the Friedman test and diagnostic analysis to discuss data and test hypotheses. Their findings shed light on a significant pattern, indicating that a majority of users, before making purchases, engage in searching and comparing desired products or services on commercial websites. Surprisingly, despite online research, these customers prefer to make their actual purchases from physical markets (Sameti, Khalili, & Sheybani, 2016).

The results of Rajendran, Wahab, Ling, and Yun (2018) also showed a positiveinfluence on the level of satisfaction. Among the main factors that positively influence customersatisfaction in E-commerce are service recovery, delivery service, and customer service. However, the number of retailers continues to increase, which increases competition among participants. Therefore, customer satisfaction is a necessity for buyers through good service. Furthermore, retailers also need to ensure that customers are not only satisfied with their purchases, that is, with the products, but also with the logistics services, as this would also attract new customers. For future directions, it is necessary that e-commerce also guarantee a tracking delivery service.

3 METHODOLOGY

This study was conducted through archival research and is characterized as experimental (Libby, Bloomfield, & Nelson, 2012). The data refers to the Brazilian E-Commerce Public Dataset available by Olist Store at the online community of data scientists and machine learners

– Kaggle. The database contains records of the year 2016 to 2018 made at multiple marketplacesin Brazil. In addition, the data has been anonymized contains real business data, and has information from over 100,000 orders (Kaggle, 2019). Figure 1 shows the multiple datasets anddatasets used in this research.
We filtered data for orders that had (i) order_status equal delivered, (ii) carrier lead-time greater than 0, (iii) delivered lead-time greater than 0, (iv) total estimated lead time greater than 0, (v) shipping timing greater than 0, (vi) price greater than 0, (vii) payment value greater than 0, (viii) freight value greater than 0, and (ix) operation lead time date greater than 0. Thus, the total of observations was equivalent to 107,762. As the purpose was the consensus analysis, we considered the selected variables by the mean, with a total of 2,935 observations.

To calculate the consensus, the review scores of each seller were used and calculated asdescribed in Equation 1.

$$Cns(X) = 1 + \sum_{i=1}^{n} p_i Log_2\left(1 - \frac{|X_i - \mu_X|}{d_X}\right) \quad (1)$$

Where;
X_i is the review score on an ordinal scale from 1 to 5 stars.
μ_X It is the average of the review scores for each seller.
d_X Refers to the amplitude scale, equal to 4.
p_i It is the probability associated with each review score for each seller.

The first model has dependent variables synthesized by the ADRIANA method. This method has foundations based on Richard Thaler's behavioral accounting, as the theory of perspectives is highlighted. This method adds to the prospect theory the assumption of deviation from a reference point can be understood as gains and losses. In this sense, the method requires that the valuation be carried out considering the objectives, as individuals can approve or disapprove of each transaction (Thaler, 2019), and in the ADRIANA method, it is considered an acquisition and not an acquisition (Hein, 2020).

*Corresponding Author: **Adhmir Renan Voltolini Gomes.**

Equation 2 describes the calculation of the ADRIANA method.

$$ADRIANA_i = \lambda A_i + (1 - \lambda)NA_i; \lambda = \lambda_a; (1 - \lambda) = \lambda_t; \lambda \in [0,1] \quad (2)$$

Where the value of λ in this study is equal to 0.5. And A_i refers to the acquisition matrixdescribed in Equation 2.1.

$$A_i = \sum_{j=1}^{n} w_j a_{ij} \quad (2.1)$$

Where w_j are the weights that in this study were assigned proportional values to the numbers of criteria. And, a_{ij} refers to the normalized observations. The non-acquisition matrixis described in Equation (2.2)

$$NA_i = \sum_{j=1}^{n} w_j t_{ij} \quad (2.2)$$

Where t_{ij} is described in Equation 2.3.

$$t_{ij} = x_{ij} - \left(\frac{[(\sum_{j}^{n} x_i) - x_{ij}]}{m-1}\right) \quad (2.3)$$

And, x_{ij} refers to each normalized observation and m refers to the number of observations for each criterion. This method can be calculated through the application available at https://performancemeasures-adriana.streamlit.app/.

The second model of this study was calculated using the Distance-Based Assessment method of the Average Solution (EDAS), this method is intended to be an alternative for solving multicriteria problems, as it is a method that selects the best-verified alternative about the distance from the mean. In this sense, EDAS considers the positive distance from the mean andthe negative distance from the mean. Thus, it describes the divergence between each alternativeverified about the average solution, so that this evaluation is carried out considering the highest values and lowest values (Ghorabaee et al., 2015) Equation 3 describes the EDAS method.

$$EDAS_i = \frac{1}{2}(NSP_i + NSN_i) \quad (3)$$

Where NSP_i is described according to Equation 3.1.

$$NSP_i = \frac{\left(\sum_{j=1}^{m} w_j \left(\frac{max\left(0, \left(\left(\frac{\sum_{i=1}^{n} X_{ij}}{n}\right) - X_{ij}\right)\right)}{\left(\frac{\sum_{i=1}^{n} X_{ij}}{n}\right)}\right)\right)_{ij}}{max_i\left(\left(\sum_{j=1}^{m} w_j \left(\frac{max\left(0, \left(\left(\frac{\sum_{i=1}^{n} X_{ij}}{n}\right) - X_{ij}\right)\right)}{\left(\frac{\sum_{i=1}^{n} X_{ij}}{n}\right)}\right)\right)_{ij}\right)_i} \quad (3.1)$$

And NSN_i is described according to Equation 3.2.

$$NSN_i = 1 - \frac{\left(\sum_{j=1}^{m} w_j \left(\frac{max\left(0, \left(X_{ij} - \left(\frac{\sum_{i=1}^{n} X_{ij}}{n}\right)\right)\right)}{\left(\frac{\sum_{i=1}^{n} X_{ij}}{n}\right)}\right)\right)_{ij}}{max_i\left(\sum_{j=1}^{m} w_j \left(\frac{max\left(0, \left(X_{ij} - \left(\frac{\sum_{i=1}^{n} X_{ij}}{n}\right)\right)\right)}{\left(\frac{\sum_{i=1}^{n} X_{ij}}{n}\right)}\right)\right)_{ij}} \quad (3.2)$$

Where Xij refers to each observation of each criterion, n Equal to the observation number. This method can be calculated through the application available at https://performancemeasures-edas.streamlit.app/.

The third model was calculated according to the DP2 method of Trapero (1977) this method allows the interspatial and intertemporal comparison of variables. The DP2 method also allows you to assign a score and rating to the elements according to the criteria. Furthermore, the advantage of this method is the opportunity to measure the disparity between the elements. Therefore, the method is built based on the premise of completeness, that is, due to the need for the components to cover the properties related to the object under analysis. And, on the linearity premise, which is associated with the linear relationship between the components (Trapero, 1977), expressed by Equation 4.

$$DP_2 = \sum_{j=1}^{n} \frac{d_j}{\sigma_j}\left(1 - R^2_{j, j-1, j-2, \ldots, 1}\right), \text{ with } R_1^2 = 0 \quad (4)$$

Dividing the distance d_j by the standard deviation (σ_j) of the component j, the indicator loses the units by which it was measured, and it solves the problem of the heterogeneity of themeasurement units, therefore, it can be used as a weighting mechanism to give less relevance to the distances corresponding to components where the values are more dispersed about the mean. Thus, the factor ($1 - R^2$) avoids duplication of information (Trapero, 1977). This method can be calculated through the application available at https://performancemeasures-dp2.streamlit.app/.

In this way, to analyze the consensus of consumer reviews we used the Kaggle platform, through a phyton language with pandas and NumPy libraries. And, to analyze the odds ratio between Adriana, DP2, and EDAS multicriteria methods and consumer satisfaction, the review score was used as the dependent variable. As explanatory variables were estimated: (i) group 1

- payments; (iii) group 2 - managerial; (iii) group 3 - operational and (v) early or delayed. In the multicriteria methods data analysis, we used the Spyder application in Python language and the following libraries: pandas and NumPy. Therefore, to estimate the odds ratio of occurrence between the independent variables (Adriana, DP2, and EDAS) and the dependent variable (review score) we used logistic regression models.

The model chosen was the logistic regression model because allows analyzing the chances of an event occurring about another (Fávero, Belfiore, Silva, & Chan, 2009) described in the Equation.

$$f(pCsn) = \left(\frac{1}{1 + e^{-(pCsn)}}\right) \quad (5)$$

$$pCsn = ln\left(\frac{p}{1-p}\right) = \alpha_0 + \beta_1 ADRpymt + \beta_2 ADRmmg_{it} + \beta_3 ADRopr_{it} + \beta_4 EarlyDelay_{it} + \varepsilon_i \quad (5.1)$$

$$pCsn = ln\left(\frac{p}{1-p}\right) = \alpha_0 + \beta_1 DP2pymt + \beta_2 DP2mmg_{it} + \beta_3 DP2opr_{it} + \beta_4 EarlyDelay_{it} + \varepsilon_i \quad (5.2)$$

$$pCsn = ln\left(\frac{p}{1-p}\right) = \alpha_0 + \beta_1 EDASpymt + \beta_2 EDASmmg_{it} + \beta_3 EDASopr_{it} + \beta_4 EarlyDelay_{it} + \varepsilon_i \quad (5.3)$$

All variables that make up the latent variables of the multi-criteria methods were normalized as follows:

$$xnorm = \frac{(x_{ij} - max_j)}{(max_{ij} - min_j)} \quad (6)$$

The variables of these models are contained in Table 1.

*Corresponding Author: **Adhmir Renan Voltolini Gomes.**

Table 1 Description, columns, and datasets

Statement	Description	Value	Variables
Votes ranging from 1 to 5 are given by the customer on satisfaction survey.	Review score multiplied by a consensus	1 above the median, and 0 otherwise	$pCsn$
Group 1 – Payment	Payment value	Mean	$ADRpymt$, $DP2pym$, and $EDASpymt$
	Price	Mean	
	Freight value	Mean	
Group 2 – Management	Operation Lead time	Mean	$DRmng$, $DP2mng$, and $EDASmng$
	Shipping timing	Mean	
	Quantity of reviews	Sum	
Group 3 – Operational	Carrier lead time	Mean	$ADRopr$, $DP2opr$, and $EDASopr$
	Delivered lead time	Mean	
	Total estimated lead time	Mean	
Early or delay	Early or Delay	Mean	$EarlyDelay$

Source: Authors (2021).

For data analysis, logistic regression models were used. This is a technique that makes it possible to analyze the odds ratio of the occurrence of a given event about the dependent variable. Thus, the result shows how many times it is possible to increase or decrease the chances of occurrence of the respective event in the dependent variable. As the dependent variable is categorical, in this article it is defined by the median of consumer reviews (1 above the median, and 0 otherwise).

4 RESULTS AND DISCUSSION

This section encompasses statistical correlations, boxplot graphs, and logistic regressions.

4.1 Descriptive analysis

To justify the use of consensus instead of the review score, Figure 1 demonstrates the boxplot plots of both variables.

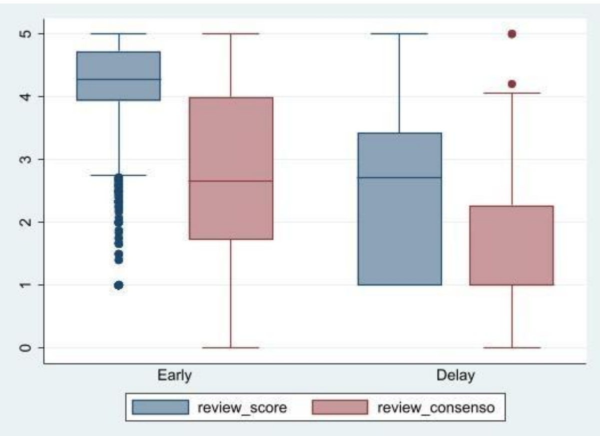

Figure 1 Review boxplots calculated by consensus and review score.

Source: survey data (2021).

Boxplots illustrate notable distinctions in ranges between quartiles. Notably, delayed deliveries align with lower review scores. However, consensus mechanisms align votes and impart greater stability to sellers' averages. Consequently, consensus adjustments accommodate variations in ordinal scores, rendering assessments more robust in terms of reviews by correcting asymmetries in the evaluated grades. According to the groups of variables, the multicriteria techniques were calculated. The Figure describes the correlation between all groups between the methods.

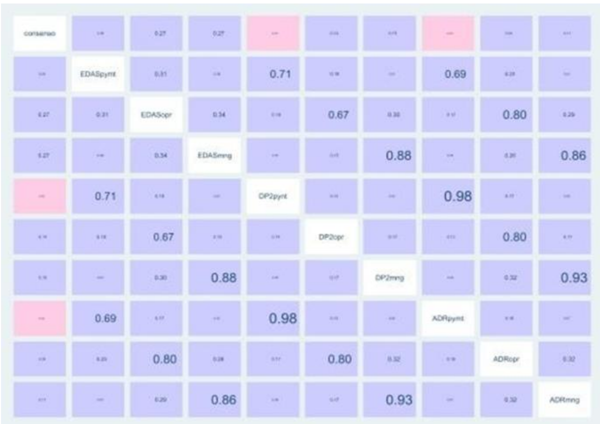

Figure 1 Correlation matrix between the multicriteria groups

Source: survey data (2021)

The most robust correlations identified exist between methods assessing identical variables, hence the exploration through various models. Additionally, there are noticeable low correlations observed among observations related to variables synthesized by the multi-criteria model, along with low correlation with the consensus variable.

4.1 Logistic regression models

Table 1 describes the results of the estimated logistic regression model for the Adriana multicriteria method. That model presented a pseudo-R2 of 3.66% with 2,930

*Corresponding Author: **Adhmir Renan Voltolini Gomes.**

observations. And, all coefficients showed statistical significance, except the constant, demonstrating that the variables synthesized by the Adriana multicriteria method change the odds ratio of the review consensus.

Table 1 – Adriana multicriteria method

Consensus	Ratio	Std. Err.	z	P > | z	[95% Conf.	Interval]
ADRIANA Payments	0.392219	0.132147	-2.78	0.005	1.734	71.747
ADRIANA Operations	18.25337	6.289852	8.43	0.000	0.000	0.003
ADRIANA Management	1.74822	0.201629	4.84	0.000	0.000	0.001
Constant	1.038464	0.040924	0.96	0.338	0.380	0.553

Source: Research data (2020)

As per the analyzed odds ratios, the Adriana multi-criteria method, when associated with payment variables, diminishes the likelihood of a consensus above the median assessments by approximately 61% (1-0.392219). Conversely, the coefficients of other variables exhibit odds ratios that elevate the chances of a consensus exceeding the median, with values of 17.25 (18.25337-1) for operations and 74.82% (1.74822-1) for management. These findings contribute significantly to discussions on consumer satisfaction, emphasizing the critical role of processes established between purchase orders and the delivery of purchased items in shaping consumer contentment (Mohamed & Coutry, 2015; Kabra & Holani, 2019; Vasić et al., 2021).

Considering Wierman and Tastle's proposition (2007) regarding the foundation that consensus offers for the obtained average, given its potential as a criterion for variability, these results underscore the feasibility of estimating the likelihood of consensus occurrences to comprehend this subject. For a thorough quality analysis and result adjustment, Figure 1 illustrates the Receiver Operating Characteristic Curve (ROC).

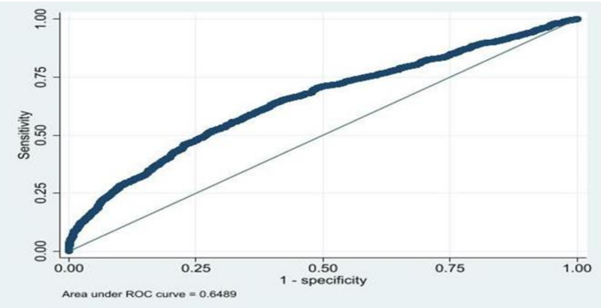

Figure 1 – ROC to Adriana multicriteria method in the face of consensus

Source: Research data (2024)

ROC presents the predicted versus the observed classification, and the result of the area under the ROC curve equals 0.64 means that the model has acceptable discrimination (Fávero et al., 2009).

Table 2 describes the results for the model EDAS multicriteria method and presents a pseudo R2 of 9.39% with 2,930 observations. In that case, the EDAS coefficients associated with the management and operation variables presented statistical significance, demonstrating that the EDAS multicriteria method changes the odds ratio of the consensus of the review. Also, as in the model of the Adriana multicriteria method, the likelihood ratio test (Table 2), analogous to the F test, indicates that the variables aren't statistically equal to zero.

Table 2 – EDAS multicriteria method

Consensus	Ratio	Std. Err.	z	P > | z	[95% Conf.	Interval]
EDAS Payments	0.708271	0.221936	-1.1	0.271	0.383245	1.308949
EDAS Operations	544.0691	276.2162	12.41	0.000	201.1458	1471.625
EDAS Management	17.9296	5.767169	8.97	0.000	9.545011	33.67945
Constant	0.00583	0.001928	-15.56	0.000	0.003049	0.011145

Source: Research data (2024)

Table 2 reveals that while the EDAS coefficients linked with operational and management variables demonstrated statistical significance, the EDAS payment variables did not. The odds ratios significantly elevate the likelihood of votes surpassing the consensus median, particularly for operational variables. This outcome adds value to the existing literature on the application of the EDAS multi-criteria method (Ghorabaee et al., 2015) by illustrating its potential to influence the probability of consensus occurrences. It underscores the importance of not only continually striving for enhancements in management processes but also emphasizes how analyzing the consensus of assessments can afford managers a more comprehensive understanding of assessment consistency.

In this scenario, the isolated analysis of estimated online purchasing processes (EDAS operations) resulted in favorable contributions to consumer satisfaction in evaluations, as the odds ratio signified an increase in the likelihood of reaching a consensus on heightened consumer satisfaction. These findings enrich the ongoing discourse initiated by Mohamed andCountry (2015), Kabra and Holani (2019), and Vasić et al. (2021), emphasizing that when scrutinizing online purchasing processes independently within payment, managerial, and operational stages, the odds ratio of the methods tends to decrease, subsequently diminishing the prospects of consumer satisfaction. Figure 2 illustrates the Receiver Operating Characteristic (ROC) curve for the EDAS multicriteria method model.

*Corresponding Author: **Adhmir Renan Voltolini Gomes.**

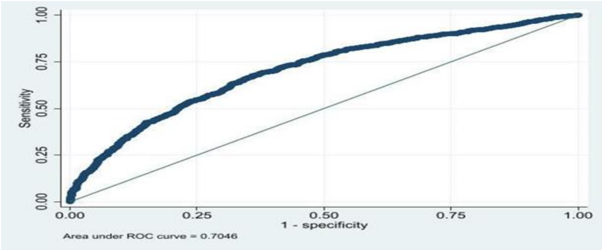

Figure 2 – ROC to EDAS multicriteria method in the face of consensus

Source: Research data (2024)

Figure 2 showcases the Receiver Operating Characteristic (ROC) with an area under the curve equal to 0.70, signifying that the model exhibits acceptable discrimination (Fávero et al., 2009). Table 3 provides a summary of the results for the DP2 multicriteria method model, revealing a pseudo-R2 of 7.44% based on 2,930 observations. In this model, all coefficients associated with DP2 demonstrated statistical significance with a p-value < 0.01. This indicatesthat the DP2 multicriteria method alters the odds ratio of consensus reviews more effectively than the ADRIANA and EDAS methods. Additionally, analogous to the F test in previous models, the likelihood ratio test (Table 3) indicates that the variables are not statistically equalto zero.

Table 3 – DP2 multicriteria method

Consensus	Ratio	Err. Std.	z	P > | z	[95% Conf.	|Interval]
DP2 Payments	0.901477	0.024027	-3.89	0.000	0.855593	0.949822
DP2 Operations	1.712157	0.074618	12.34	0.000	1.571981	1.864833
DP2 Management	1.189016	0.03074	6.7	0.000	1.130269	1.250817
Constant	2.36E-11	4.65E-11	-12.42	0.000	4.97E-13	1.12E-09

Source: Research data (2020)

Table 3 shows that although the DP2 coefficients presented statistical significance, the results for the odds ratio are divergent. That means the coefficient associated with managementand operations variables increases the chances of a consensus. On the other hand, the coefficient associated with payments reduces (1 – 0.958) the chances of a consensus. In that sense, it is observed that those results can contribute to the evidence of Mohamed and Country (2015) and Kabra and Holani (2019), and Vasić et. al (2021) by demonstrating that the management and logistics steps of the online purchase process are determinant in consumer satisfaction. In that case, those steps can contribute to the chances of consumer satisfaction.

Table 3 shows that although the DP2 coefficients presented statistical significance, the results for the odds ratio are divergent. This means that the coefficient associated with the management and operations variables increases the chances of consensus greater than the median. On the other hand, the coefficient associated with payments reduces (1 – 0.901477) thechances by approximately 10%. In this sense, it is observed that these results can contribute to the evidence from Mohamed and Country (2015) and Kabra and Holani (2019), and Vasić et. al (2021) by demonstrating that the management and logistics stages of the online purchasing process are decisive in consumer satisfaction. In this case, these steps can contribute to the chances of consumer satisfaction.

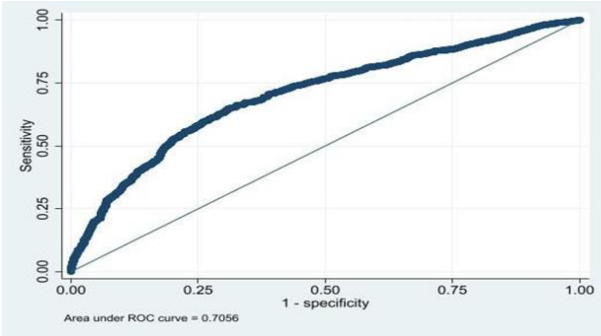

Figure 3 – ROC to DP2 multicriteria method in the face of consensus

Source: Research data (2024)

Figure 3 displays the Receiver Operating Characteristic (ROC) for the DP2 multicriteria method concerning consensus, revealing an area under the ROC curve equal to 0.70. This result indicates that the model exhibits acceptable discrimination, as per the criteria outlined by Fávero et al. (2009). Consequently, the findings of this study underscore the significance of employing multicriteria methods in the analysis of company operations. Such methods have the potential to influence the occurrence of consensus in customer reviews and identify inconsistencies in constructing a consensus within those reviews.

5. CONCLUSION

The main objective of this article was to analyze the odds ratio between the purchase order processes and product delivery and the consensus of consumer evaluations in e-commerce. The analysis revealed that the results generated by multi-criteria methods exert a discernible influence on the probability of reaching consensus in consumer evaluations.

These conclusions highlight the importance of consensus analysis in customer evaluations, emphasizing its relevance for making managerial decisions that aim to increase efficiency in the period between the purchase order date and the product delivery date. Furthermore, the results emphasize the critical importance of meeting defined deadlines to maintain consumer trust, as any deviation directly impacts the review score. Therefore, it becomes clear that it is essential to achieve not only a high average but also a consensus in consumer evaluations.

These findings contribute significantly to the consumer satisfaction discourse by offering an alternative perspective through a consensus-focused analysis. Taking advantage of multi-criteria methods and consensus analysis provides a differentiated understanding of data, offering valuable insights

*Corresponding Author: **Adhmir Renan Voltolini Gomes.**

that can be fundamental to improving company management processes. The impact is twofold: First, stakeholders, from manufacturers and distributors to consumers, gain a more reliable means of assessing satisfaction with product attributes. Second, it sheds light on the efficiency of logistics partners, potentially influencing consumers' purchasing decisions and rewarding the most efficient partners.

Recognizing the limitations, this study treated the dependent variable as categorical, despite its 5-point amplitude, like the Likert scale. Although the scale ranges from 1 star denoting a lower rating to 5 stars representing a higher rating, the ranges between values are not considered uniformly equal (Jamieson, 2004). Furthermore, the study did not cover the measurement of all attributes that contribute to consumer satisfaction. Future research efforts could focus on classifying and identifying groups of common attributes within specific segments to deepen our understanding of consumer satisfaction.

REFERENCES

1. Afridola, S., & Hikmah, H. (2018). The Comparison of Level of Costumers Satisfaction Toward an Interpersonal Communication Ojek Online and Offline in Batam. *Jurnal Apresiasi Ekonomi*, 6(2), 152-161. DOI: 10.31846/jae.v6i2.75. Available at: <http://stiepasaman.ac.id/ojsapresiasiekonomi/index.php/apresiasiekonomi/article/view/7 5>
2. Arinda, F., Soetjipto, B. E., & Hermawan, A (2018). The Effect of Product Quality, Brand Image, and Menu Variety on Customer's Loyalty Through Customer's Satisfaction as An Intervening Variable. *European Journal of Business and Management*. 10(11), 175-184. DOI: Available at: <https://pdfs.semanticscholar.org/171a/b866a94297 18c87bd8a5fd40d2203fc19ddf.pdf>
3. Bhaskar, P. P., & Kumar, D. P. (2016). Customer loyalty on e-commerce. International Journal of Management Research and Reviews, 6(12), 1661-1668.
4. Darko, S., Terkper, V. D., Novixoxo, J. D., & Anning, L. (2018). Assessing the effect of lead time management on customer satisfaction. 6(1), 1-22.
5. Delima, A., Ashary, H. M., & Usman, O. (2019). Influence of Service Quality, Product Quality, Price, Brand Image, and Promotion to Consumer Satisfaction Affecting on Consumer Loyalty (Online Shop). *SSRN*. DOI: http://dx.doi.org/10.2139/ssrn.330870 Available at:<https://ssrn.com/abstract=3308707>
6. Di Fatta, D., Musotto, R., & Vesperi, W. (2016). Analyzing e-commerce websites: A quali-quantitative approach for the user-perceived web quality (UPWQ). *International Journal of Marketing Studies, 8*(6), 33-44. http://dx.doi.org/10.5539/ijms.v8n6p33
7. Fávero, L. P., Belfiore, P., Silva, F. D., & Chan, B. L. (2009). Análise de dados: modelagem multivariada para tomada de decisões. Rio de Janeiro: Campus.
8. Ghorabaee, M., K., Zavadskas, E. K., Olfat, L., & Turskis, Z. (2015). Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS). *Informatica*, *26*(3), 435-451.
9. Hein, N. (2020). Análise Decisória Relativa Interativa de Aquisição e Transação. Ágora: *Revista de Divulgação Científica*, *25*, 133–151. https://doi.org/10.24302/agora.v25i0.2974
10. Jamieson, S. (2004). Likert scales: how to (ab) use them. *Medical education*, 38(12), 1217- 1218.
11. Kabra, V., & Holani, U. (2019). An overview of consumer satisfaction towards online and offline shopping through supermarket/hypermarket. *Journal of Management Value & Ethics*, 9(1) 39-48.
12. Kaggle (2019). *Brazilian E-CommercePublicDataset by Olist*. Available at: <https://www.kaggle.com/olistbr/brazilian-ecommerce>
13. Libby, R., Bloomfield, R., & Nelson, M. W. (2002). Experimental research in financial accounting. *Accounting, Organizations and Society*, *27*(8), 775-810.
14. Mohamed, A. A. M., & Coutry, N. (2015). Analysis of lead time delays in supply chain: a case study. *International Journal of Economics and Management Engineering*, 9(6), 2065- 2070.
15. Rajendran, S. D., Wahab, S. N., Ling, Y. W., & Yun, L. S. (2018). The Impact of Logistics Services On the E-Shoppers' Satisfaction. *Int. J Sup. Chain. Mgt*,*7*(5), 461-469.

*Corresponding Author: **Adhmir Renan Voltolini Gomes.**