International Joint Conference on Industrial Engineering and Operations Management- ABEPRO-ADINGOR-IISE-AIM-ASEM (IJCIEOM 2020)

Measurement of efficiency for e-commerce customer service under data envelopment analysis

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Abstract Data Envelopment Analysis (DEA) is a method for measuring the efficiency of decision processes which has multiple sources (inputs) to be reduced and outcome (outputs) variables to be increased. This paper employs DEA to assess efficiencies amongst e-commerce's customer services teams. Due to the COVID-19 pandemic, many consumers are buying in online stores, standing out this kind of enterprise service. An area of development in recent years has been devoted to applications of DEA which performs measurements using, simultaneously, the increasing of desirable outputs and decreasing of undesirable output for the operational efficiency of decision-making units (DMUs). The model was chosen because it can cover the outcome of legal fees of a company, which is expected to be reduced due to financial expenses and the image of a corporation. The objective is evaluating the operational performance of different teams in the company to measure the teams which are not performing well in relation to the others and how much each one must improve to become efficient.

Keywords: data envelopment analysis; customer service; operational excellence;

1 Introduction

Retail commerce is passing through significant changes due to digital innovations, with the migration of physical stores to e-commerce sales being frequent, and in particular, marketplace platforms. Especially in quarentine times, this business model is based on a set of stores, which seek greater visibility in their products. The platforms collect exhibition fees without the burden of delivery and storage costs. However, this generates excess demand for work in corporate areas such as customer service and logistics.

Thus, it is necessary to establish more efficient ways of producing with the least possible impact on resources. According to Porter and Van der Linde (1995) this is an important strategic advantage in a competitive market. From this context, there is the challenge of maintaining the best possible satisfaction relationship with consumers even after possible conflicts caused by process flaws.

Data Envelopment Analysis (DEA) is a non-parametric method that identifies good practices among decision-making units (DMUs) that have multiple inputs and outputs variables. An important model of DEA is the use of Directional Distance Functions (known as DDF model), which has been used to model resources of production processes in the presence of undesirable outputs and output assessments (Chung et al. 1998)

The paper evaluates the service efficiency of the different channels of communication with the customer that an e-commerce company has. These channels will be studied as DMUs. The DDF model was chosen because it is a variant of the DEA that simultaneously explores the expansion of desirable outputs and the contraction of undesirable output as well as input. Such metrics were chosen as they are connected to the company's strategic objectives, in this work metrics were selected linked to the financial and retention objectives of the platform user as a customer.

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In section 2, the DEA model as well as the DDF model will be presented. In section 3, is specified how the work was prepared. In the following, 4, the DEA model adapted to the case study and the analysis of the results obtained are shown. In the last section 5, the final comments and suggestions for future studies.

2 Data Envelopment Analysis and Directional Distance Function

Data Envelopment Analysis (DEA) is a non-parametric approach to efficiency measurement proposed by Charnes et al. (1978) which mathematical programming models achieves the relative performance of DMUs that are comparable to each other using multiple inputs to produce multiple outputs (Cooper et al., 2007). DEA has some advantages over conventional performance measurements. The efficiency frontier, which represents best practices, is built on DMUs that use low measurements of input compared to outputs or high measurements of outputs compared to inputs.

The result is an efficient Pareto frontier, in which the DMUs located has a 100% rate. In general, the models have dual formulations (envelopment and multipliers), with two possible radial orientations: the inputs, which seek to minimize the resources used, keeping production levels unchanged; and outputs, which implies an increase in production without changing the quantities of inputs used (Rubem et al., 2014).

As the objective is the ordering of the units, according to their performance, in which the CCR (Charnes et al., 1978) and BCC (Banker et al., 1984) output-oriented models are equivalent. The model with unitary input, oriented to outputs, in the formulation of the envelope is given by:

$$\begin{aligned}
&\text{Max } h_o \\
&\text{sujeito a} \\
&\textstyle\sum_{k=1}^{n} \lambda_k y_{jk} \geq h_o y_{j0}, \forall j \\
&\textstyle\sum_{k=1}^{n} \lambda_k \leq 1 \\
&\lambda_k \geq 0, \forall k
\end{aligned} \quad (1)$$

where *h*o is the inverse of the efficiency of the DMU under analysis (DMUo); y_jk is the j-th output (j = 1, ..., s) of the DMUk (k = 1, ..., n); and ʎ_k is the contribution of each DMU in forming the target of the DMUo. This model can be interpreted as an additive multicriteria model in which the alternatives (DMUs) assign weights to the criteria (outputs), ignoring any decision value of the decision maker. Under such conditions, it can be said that the DEA model is used more as a multicriteria tool, rather than as an instrument for calculating an efficiency measure (Gomes et al., 2012). For more information on this type of model, see Cook and Zhu (2005).

Golany and Roll (1989) presented a description of the DEA methodology which establishes three phases in which are: definition and selection of DMU to be analyzed, selection of variables (inputs and outputs), which are relevant to establish the efficiency of DMUs and the application of DEA models.

The first phase aims at determining the set of homogeneous DMU to be evaluated. Regarding the selection of variables (second phase), this can be done in two ways. The first uses the opinion of the interested party or the specialist, who must take into account: if the variable is providing necessary information that has not been included in other variables, if the variable is contributing to one or more objectives of the application, if the data of the variable is reliable and safe and if it explains the efficiency of a DMU and if there is a causal relationship between each input / output pair. The third phase involves first choosing the orientation of the model, which allows establishing the objective of the study. If an input orientation is chosen, this will indicate that the objective will be to reduce the inputs (inputs used) that can be obtained without changing the level of current outputs (the quantity of "products"). The output orientation indicates that the purpose will be to maximize the outputs that can be obtained (maximize the products) without increasing the level of inputs used (the amount of inputs used).

The DDF is a DEA variant that an output can be used to be reduced. The model can be represented, in general, according to the model (1) below. Where g_x and g_y are the direction vectors associated with inputs x and outputs y. The objective function β is a measure of inefficiency.

$$\begin{aligned} & \max \ \beta \\ & s.t. \ X\lambda + \beta g_x \leq x_0 \\ & \quad Y\lambda - \beta g_y \geq y_0 \\ & \quad \lambda \geq 0 \\ & \quad g_x \geq 0, g_y \geq 0 \end{aligned} \tag{2}$$

The use of undesirable outputs, as shown in model 2, the distinction of the outputs shown in (2) is added: desirable represented by Y; undesirable by β. Also adding the direction vector g_b, associated with the undesirable output, which can be negative, showing that the reduction of the indicator indicates greater proximity to the efficiency frontier.

$$\begin{aligned} & \max \ \beta \\ & \text{s.t.} \ X\lambda + \beta g_x \leq x_0 \\ & \quad Y\lambda - \beta g_y \geq y_0 \\ & \quad B\lambda - \beta g_b = b_0 \\ & \quad \lambda \geq 0 \\ & \quad g_x \geq 0, g_y \geq 0, g_b \leq 0 \end{aligned} \tag{3}$$

In general, β represents the parameter of the decision-making unit could reduce undesirable outputs, maintaining its value at the observed level. It can be interpreted as the number of units of each type of input or output that can be decreased or increased, respectively. The higher the β value are, the further the input or output of the analyzed DMU is in relation to the benchmark, being a measure of inefficiency.

Although β represents a measure of inefficiency, it is not compatible with the inefficiency measures produced by the radial and Slacks Based Models because β can be greater than 1. This incompatibility is eliminated only when gx = x0, gy = y0 and gb = b0. Thus, when the direction vectors are considered equal to the observed inputs and outputs, the DDF is equivalent to a radial model. Assuming that undesirable outputs are not present, DDF is equivalent to the input-oriented radial model if gx = x0 and gy = 0. If gx = 0 and gy = y0, the DDF considered is equivalent to the output-oriented radial model (Chambers , et al., 1998).

Cheng and Zervopoulos (2014) used directional distance functions to extend the nonparametric frontier approach for measuring efficiency over health system service evaluation. In which they incorporate both desirable output (life expectancy) and undesirable (infant and maternal mortality rate) in the measurement without transforming the latter into input or in its inverse form. Such methodology introduces a modification of the efficiency result, which produces consistent results in comparison to those obtained from radial models and also, regardless of the length of the direction vector.

Another application of the DDF model in services can be seen in the analysis of air service efficiency. In this case, Fan et al. (2014), evaluated the efficiency of 20 Chinese airports (DMU) and compared the results with and without the use of undesirable output (flight delays). Several DMUs have undergone significant changes in their efficiency after considering undesirable outlets.

3 Case Study

According to Mittal et al. (2005), companies that are successful in both customer satisfaction and high productivity in customer service management, reaches greater long-term financial performance than those that reaches only customer satisfaction or high management productivity.

Based on research by Jochen Wirtz (2017), outcomes showed that service excellence can be achieved through three main strategies. First, a dual culture strategy provides a comprehensive set of high-quality, low-cost services, driven in large part by the multidisciplinarity of leadership in the context of new practices available. Second, an operations management approach reduces process variability and thus allows for increased use of systems and technology to achieve excellence. Third, a focused service factory strategy can provide a single type of service for a highly focused customer segment.

To carry out the study, the software LINDO was used for mathematical modeling. For reasons of secrecy, we will call the company C3. The study is based on a total of 129,360 cases of assistance in the period of one week of the company. The company has a total of 1,600 employees in the customer service sector.

This sector consists of 14 different service channels where consumers can access and register complaints. These channels will be the DMU's to be analyzed in the model. The company wants to improve the service level in this segment in order to meet the needs of consumers and competitiveness in relation to competitors.

Following the perspective of concentrating efforts and resources on the most dominant problems, it is necessary to know which service team needs more attention regarding the performance indicators measured by the organization. First, a process mapping of the service steps was carried out. Fig. 1, outlines the service process that occurs in all channels, using a SIPOC matrix, which maps suppliers, inputs, process, product and consumers of each stage, offering a broad view of the service process.

Suppliers	Inputs	Process	Outputs	Customers
Consumer	Complaint	Receive the complaint	Complaint registered in application system	Consumer Services Area
Application System	Detailed complaint	Analyse the complaint	Resolution or sending to the responsible area	Consumer or responsible area
Responsible area / Consumer services area	Proposals and negotiations	Resolve the complaint	Complaint resolved	Consumer
Consumer services area	Complaint resolved	Finish the complaint	Completed complaint and performance indicators	Consumer and C3

Fig. 1 Service Flow SIPOC Matrix

The 4 variables to be studied are based on the model of financial benefit and productivity of Wirtz (2018), in which the indicators should reflect together the company's financial performance and gains:

1. Complaint: the occurrence shown in Fig. 1;
2. Attendants: number of workers who work exclusively to answer customer complaints;
3. Solved cases: number of complaints that were resolved by the attendants, may take different times between different DMU's;

4. Cases leaked to external channels: occurs when the consumer, dissatisfied after opening a complaint at C3 and not having the case resolved, opens a complaint with an external inspection institution. The most common are PROCON, Special Civil Court and Reclame Aqui. Such instances create negative repercussions and the application of fines and legal fees, which is considered an important factor for the company.

3.1 DEA application

The data for evaluation are shown in Table 1, with the number of complaints, attendants, resolved cases and leaks. The first two being the inputs, the third the output and the last, the undesirable output. It should be noted that the sum of the last two variables does not necessarily result in the number of complaints, since sometimes the customer can complain more than once on an external channel. This can occur when consumer is very dissatisfied or when the case begins to take time to resolve. It was decided to account for leaked cases more than once, as different legal processes can generate more fines and fees.

Table 1 Inputs and outputs data

L	DMU	Complaints	Attendants	Solved Cases	Leaked Cases
1	Chat	69.092	524	68.902	298
2	Voice	12.376	298	12.256	213
3	Specialist Chat	10.178	64	10.168	16
4	Specialist Voice	8.009	185	7.910	195
5	E-mail	4.671	181	4.550	134
6	Physical stores	3.737	65	3.697	62
7	Facebook	3.524	5	3.501	26
8	Twitter	3.154	4	3.090	101
9	Site	2.948	51	2.894	77
10	Application	2.937	48	2.901	77
11	Crossborder	2.389	59	2.341	54
12	Specialist E-mail	2.380	52	2.302	98
13	Whatsapp	2.041	59	2.004	53
14	Ombudsman	1.924	5	1.924	28

3.2 Results

With the model presented in (1) and (2), and the variables described in the previous section, the results presented in Table 2 were obtained using the LINDO software.

The parameter ƛ were not identified for DMUs 1, 4, 5, 6, 9, 10, 11, 12 and 13 whose columns were not shown in Table 2. Column "B", which represents β, shows the measure of inefficiency. The column "B-1" shows efficiency in conventional mode, with efficient DMUs equal to 1. The ƛ, presented in section 2, show the teams that are benchmarks of the observed DMU, representing all viable combinations between DMUs.

That is, for DMU1 Chat, the benchmarks are 2, 3 and 14. But for DMU2 Voice only 14 is the benchmark. This is important for comparisons by the DMUs.

Table 2 Results obtained from the multipliers and objective function of each DMU

L	DMU	B	B-1	ʎ 2	ʎ 3	ʎ 7	ʎ 8	ʎ 14
1	**Chat**	0,001	0,999	0,521	5,482	0,000	0,000	3,544
2	**Voice**	0,005	0,995	0,000	0,000	0,000	0,000	6,401
3	**Specialist Chat**	0,000	1,000	0,000	1,000	0,000	0,000	0,000
4	**Specialist Voice**	0,006	0,994	0,000	0,000	0,000	0,000	4,140
5	**E-mail**	0,013	0,987	0,000	0,000	0,000	0,000	2,396
6	**Physical stores**	0,005	0,995	0,000	0,000	0,000	0,000	1,930
7	**Facebook**	0,000	1,000	0,000	0,000	1,000	0,000	0,000
8	**Twitter**	0,000	1,000	0,000	0,000	0,000	1,000	0,000
9	**Site**	0,009	0,991	0,000	0,000	0,000	0,000	1,518
10	**Application**	0,617	0,383	0,000	0,000	0,000	0,000	1,517
11	**Crossborder**	0,102	0,899	0,000	0,000	0,000	0,000	1,229
12	**SpecialistE-mail**	0,017	0,983	0,000	0,000	0,000	0,000	1,216
13	**Whatsapp**	0,915	0,085	0,000	0,000	0,000	0,000	1,051
14	**Ombudsman**	0,000	1,000	0,000	0,000	0,000	0,000	1,000

From the results, we verified that the C3 service system has 4 service channels (DMUs) as efficient. They are: Specialist Chat, Facebook, Twitter and Ombudsman.

DMU 1 has the highest proportion of cases resolved compared to the number of complaints. As it has the third highest number of complaints, the rate of 99.90% of solved cases is noteworthy, and the channels with the best performance considering only this item. In addition, it is the smallest number of cases leaked in absolute terms in the undesirable output of the system, as shown in Table 1. It is worth noting that the Specialist Chat are the specialized area that acquires the cases that the Chat cannot solve.

The two social media service channels stood out in the variable of number of attendants being the two lowest, together with the Ombudsman, as shown in Table 1. However, with more cases received than the latter. This fact is influenced by the fact that there were specific software for this type of service that facilitate the work of the attendants. The point to be verified is that Twitter has a high value of leaked cases.

For Ombudsman it is worth that all cases received are resolved according to the company's criteria. It could not be different, since this channel is the company's highest level of service. For this reason, the low number of undesirable output compared to the amount of inputs, since the Ombudsman team is left with the most complex problems to be solved.

Table 3 shows the efficiencies presented in Table 2 and the slacks for each variable. No values of A efficiency (B_A) and C efficiency (B_C), of Complaints and Solved Cases were identified, respectively, which indicates that both criteria were not relevant for the efficiency evaluation of the model. Unlike B efficiency, Attendants, and efficiency, Leaked Cases. These were influencers of the four efficient DMUs, and relevant to the model.

Table 3 Efficiency indicators. Source: Own elaboration.

DMU		B	B-1	B_A	B_B	B_C	B_D
1	Chat	0.001	0.999	0.000	0.000	0.000	0.000
2	Voice	0.005	0.995	0.000	264.540	0.000	32.730
3	Specialist Chat	0.000	1.000	0.000	0.000	0.000	0.000
4	Specialist Voice	0.006	0.994	0.000	163.160	0.000	77.960
5	E-mail	0.013	0.987	0.000	166.650	0.000	65.160
6	Physical stores	0.005	0.995	0.000	54.990	0.000	7.570
7	Facebook	0.000	1.000	0.000	0.000	0.000	0.000
8	Twitter	0.000	1.000	0.000	0.000	0.000	0.000
9	Site	0.009	0.991	0.000	42.940	0.000	33.780
10	Application	0.616	0.383	0.000	40.190	0.000	34.050
11	Crossborder	0.102	0.899	0.000	52.255	0.000	19.038
12	Specialist E-mail	0.017	0.983	0.000	45.052	0.000	62.308
13	Whatsapp	0.915	0.085	0.000	53.204	0.000	23.084
14	Ombudsman	0.000	1.000	0.000	0.000	0.000	0.000
General		0.121	0.879	0.000	63.070	0.000	25.406

So, all efficient DMUs (B = 0.000) also obtained a value of 0.000 for each observed efficiency, that is, they have no potential for increasing input and no potential for reducing output without changing efficiency. Efficiency (B_B) obtained an overall average of 63,070 people, that is, you can have an average of 64 fewer people in each DMU without increasing the number of Empty Cases.

Likewise, it is possible to reduce the number of Leaked Cases by 25.4 for each team with the same inputs used for assistance. An important procedural factor is that the selection processes are rigorous together with the Expert Voice and have qualified attendants in relation to the others. However, the latter team was not classified as efficient, which may be indicative of improvements in this area.

The Whatsapp area was the least efficient, with leftovers compared to the second least efficient, Application. Other DMUs with fewer attendants, are able to solve more cases than these teams, such as Facebook, Twitter and the Ombudsman. The DDF model was able to assess the efficiency of the case presented. The four teams has qualified attendants, receives big numbers of complaints, about 4.5 times more than the Ombudsman.

4 Conclusion

The application of the DDF model was useful: it was possible to insert an important productivity variable in a performance evaluation model; for checking in the model the clearances generated by each indicator; evaluate the undesirable output, showing the indicator was important and consistent in the DEA model performed; because you can choose the direction of the model and the undesirable output.

Other observation is to pay more attention to the Specialist Voice, E-mail and Specialist E-mail teams, which found a greater potential for reducing Leaked Cases using the same number of Attendants and Complaints. As Specialist Voice and E-mail also had a high potential for reduction in B_B, a need to reduce the number of attendants was identified. With this, it is possible to decrease the team and, at the same time, decrease Leaked Cases of the two DMUs. Voice can also be reduced to the frame because it obtained the highest B_B.

The existence of B_B values indicated an excess of people working in the analyzed teams and, consequently, costs. Such human resources could be used in other sectors of the company that are in need of hiring. The existence of B_D values showed that, with the same inputs, it is possible to improve operational indicators.

In this way, the objective was reached to evaluate the operational performance of the customer service teams analyzed within the company. It is hoped that this will generate improvement decisions to be made, thus causing the greatest impact on the consumer’s perception of C3's customer services, which is in line with that mentioned by Mittal et al. (2005), to ensure greater long-term performance by the corporation and to know exactly how much each non-efficient team must improve to reach the 4 DMUs identified as benchmarks.

As future studies to be developed from this work, we can add a variable for the time taken to solve cases. This was not used in the work because the number of leaked cases is the priority criterion due to the costs with fees and resulting legal expenses.

You can also integrate with other methods of analysis in DEA such as the Slacks Based Model (SBM). The work of Tone (2003), can be useful in this sense because it is also used to perform analyzes of unwanted variables, with this it would be possible to compare the results of the methods and perform a bibliographic analysis on the use of the two methods as well as negative points and positives, similarities and differences that may occur with them.

Finally, it would also be possible to carry out team sizing work with the variable Attendants using the Zero Sum Gains DEA method (Gomes et al, 2004).

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