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The Mediating Effect of the Big Data Analytics on the Relationship between Strategic Service Logistics Management and Operational Performance

O Efeito Mediador do Big Data Analytics na Relação entre Gestão Estratégica da Logística em Serviços e Desempenho Operacional

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Abstract
This paper, of exploratory nature of quantitative type, analyzed customer satisfaction in e-commerce, in particular attention on the mediating effect of the use of the Big Data Analytics in the relationship between strategic management of service logistics and operational performance. Ninety-eight questionnaires were obtained from logistics managers of e-commerce companies. The data treated by structural equation modeling, Partial Least Square, Path Modeling (PLS-PM) technique, at statistical significance level ($\alpha \leq 0.05$), revealed that the Big Data Analytics partially mediated the relationship between strategic service logistics management and logistics operational performance, in turn, positively influenced customer satisfaction. This result presented implications for the theory and management practices.
Keywords: big data analytics; strategic logistics management; logistic operational performance.

Resumo
Este artigo, de natureza exploratória do tipo quantitativo, analisou a satisfação do cliente no comércio eletrônico, em especial atenção sobre o efeito mediador do uso da *Big Data Analytics* na relação entre gestão estratégica da logística de serviços e o desempenho operacional. Foram obtidos 98 questionários junto a gestores logísticos de empresas de ecommerce. Os dados tratados pela modelagem em equações estruturais, a técnica do *Partial Least Square, Path Modeling* (PLS-PM), em nível de significância estatística ($\alpha \leq 0{,}05$), revelou que o *Big Data Analytics* mediou parcialmente a relação entre gestão estratégica da logística de serviços e o desempenho operacional logístico, por sua vez, influenciou positivamente na satisfação do cliente. Esse resultado apresentou implicações para a teoria e para as práticas gerenciais.
Palavras-chave: *big data analytics*; gestão estratégica da logística; desempenho operacional logístico.

1 INTRODUCTION

The presence of digital technology and internet connectivity has enabled the generation of new businesses such as the integration between offline and online sales. Overall, in recent years, the average annual growth of online (virtual) sales has grown, for Bragança (2019) between 15% to 30%; and for Guy (2015) between 10 to 15%

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higher than offline (physical store) sales. While Guy (2015) argues that sales in physical stores are being cannibalized by online sales; from Bragança's (2019) point of view what is occurring is an integration between offline and online sales.

Corroborating with Bragança (2019), in relation to the logistics operation, Guedes (2015) argues, that it is already discussed stores perform distribution center functions to the extent that they establish businesses of delivering products to customers, close to the store, a mile away (last-mile distribution), increasing the efficiency of online sales delivery (LIM; SRAI, 2018). In this sense, companies such as amazon, casas bahia, and ponto frio provide services in which the online shopping consumer can receive their orders in a locker available in a public or private location at 24-hour self-service stations (MILLER, 2018).

The great challenge of strategic management of logistics in services, associated with the growing use of mobile technology by consumers as a powerful tool of search and solution for purchasing choices, is to generate logistics process with services paying attention; on the one hand, to the needs and demands of consumers; on the other, to meet the goals of operational performance, in turn, ensure consumer satisfaction (MENTZER *et al*., 2001). In this sense, the market has several technological tools such as the Big Data, internet of things, machine learning and cloud computing, whose integration of these innovations are part of Industry 4.0 (FRAZZZON *et al*., 2019), to meet performance goals of the company and adequate levels of logistics services to the consumer.

Nonetheless, among these various available technologies there has been evidence, in terms of strategic logistics management in service, of the importance and use of the digital tool, Big Data Analysis (SANDERS, 2016). Data contains much value and companies need to capitalize on the variety of data sources through in-depth and proper analysis of big data.

In this context, this study's research problem was to answer the following question: Does the Big Data Analytics (BDA) mediate the relationship between Strategic Logistics Management in Service (GELS) and Logistics Operational Performance (LOP), subsequently impacting on Customer Satisfaction (CS)? The objective was to develop a measurement model, from theoretical and empirical research to examine the influence of BDA on the relationship between GELS and DOL and its effect on SC.

This paper is structured as follows. After the introduction, the theoretical framework and the hypotheses that support the study are described. Next, the methodological procedures are detailed. In item 4 the data analysis and results are described. Finally, the conclusions and suggestions for continuation are exposed.

2 THEORETICAL FRAMEWORK AND HYPOTHESES

2.1 Strategic logistics management and logistics operational performance

The main purpose of any logistics system in services is to meet the performance goals, subsequently, the customer satisfaction (CHRISTOPHER, 1997; BOWERSOX *et al*., 2014). He also adds Christopher (1997), is the main source of competitive advantage whose basis is operational efficiency. In this sense, the purpose of logistics management is to design strategies that allow the realization of superior quality service and low cost and get return on invested capital. Whittington (2002) argues that strategies are, in a certain sense, orders for others to execute, given that, in a process of fierce competition, it is the markets, and not the managers, that determine the prevailing strategies within a given environment.

For Williamson (2008) economics is the best strategy and the only real competitive advantage is relative efficiency. Managers must focus on their costs, especially those of transaction, coordination, and organization. Porter (1985), in the search for strategies that would provide superior value from the customer's perspective, presented the value chain activities view, according to which, to gain competitive advantage over its rivals it must perform activities more efficiently than its competitors in such a way that it creates more value perceived by the buyer.

Research by Lalonde and Zinszer (1976) showed that these various approaches had in common, the relationship at the buyer/seller interface, suggesting that customer service can be examined under three elements: a) pre-transaction elements. These relate to company policies or programs; b) transaction elements. These are those customer service variables directly involved in the performance of the physical distribution function and; c) post transaction elements. These are those that support the product once it is in use.

Thus, GELS is not only about the product or the price, but also about adding value and obtaining CS, which consume time and resources (NOVAES, 2015). Thus, companies have different points of view about customer services (LALONDE; ZINSZER, 1976). As a result, there are several approaches on customer services in order to meet the DOL, create value and satisfy the customer.

Thus it is to be assumed that:

H_1: strategic management of logistics in services influence on pre-transaction elements
H_2: strategic management of logistics in services influence on transaction elements
H_3: strategic management of logistics in services influence on post-transaction elements

From a GELS perspective, the firm must adopt consistent approaches to providing time and place utility in the transfer of products (CHRISTOPHER, 1997), as well as setting service priorities. Fundamentally, the service issue starts from the premise that customers and products are not equally profitable (LOVELOCK, 1983). Thus, CS is the result of all logistics activities or supply chain processes.

Thus it is to be assumed that:

H_4: strategic management of logistics in services influences logistics operational performance

2.2 Strategic logistics management and logistics operational performance, via BDA

2.2.1 Strategic Service Logistics Management and BDA

GELS has in the provision of information, accurate and updated, an essential element to provide a high level of customer service through short and consistent order cycles (BALLOU, 2006; BOWERSOX *et al*., 2014). The increasing efforts to replace resources with information, for example, replacing stocks with information sharing between functions or companies, in such a way as to reduce logistics costs, has been recurrent due to technological advances such as the ever-increasing increase in computational memory space and increasingly improved platforms for transmitting information.

As a result, it has emerged as a new frontier of digital information technology, BDA, which has become an important tool for competitive advantage. According to Sanders (2016), BDA without Analytic is a massive data set. Analytics without Big Data are simply tools and applications of mathematics and statistics. Chen *et al*. (2015) in a survey of a sample of 161 US companies revealed that the use of BDA at the organizational level affects value creation; and is moderated by environmental dynamism; technological factors directly influence the organization's use of BDA; organizational and environmental factors indirectly influence the organization's use of BDA such as proper support from top management. Collectively, these disclosures provide an understanding of the organization's use of BDA, as well as guidance on what managers should expect from using this technology.

To examine the bullwhip effect and the causes of inefficiencies in logistics and supply chain, Hofmann (2015) used Big Data and simulated various processes to improve supply chain management. The result showed that speed was the relevant dimension of supply chain inefficiency. In terms of BDA dimensions involve volume, speed and variety (SANDERS, 2016; HOFMANN, 2015). They also include in that list the dimensions truthfulness and value (WAMBA *et al*., 2016).

Regarding human skills, Mikalef *et al*. (2019) recognize that both technical and administrative skills are necessary to achieve gains from Big Data investments. Also, top management must get involved, support the implementation of BDA, identify and set priorities, and assist in problem solving (MULLER; JENSEN, 2017). Access to the necessary operational resources, such as funding and professional skills, are important to leverage BDA to its full strategic potential (MIKALEF *et al*., 2019).

Thus it is to be assumed that:

H_5: There is a positive relationship between strategic logistics management in services and BDA

2.2.2 BDA and Logistics Operational Performance

Investing in digital technologies and information systems is often justified as a strategic need to compete in a highly competitive marketplace (PORTER; HEPPELMANN, 2015). Unfortunately, many companies have failed to understand the emphasis of how to use the technology, rather than the technology itself (FAWCETT *et al*., 2011). In these fallout, of pros and cons, BDA has become an imperative for business leaders in all industry sectors (SANDERS, 2016).

The BDA can leverage competitive advantage along the entire supply chain decision spectrum, nevertheless, there is still limited understanding of how to transform the potential of the electronic tool into a noticeable and consistent result (MIKALEF *et al*., 2019). Despite positive reports of the use of BDA by pioneers, it deserves in-depth investigation into the mechanisms and processes used of the electronic tool (CHEN *et al*., 2015).

Galbraith's (1974) view based on information processing argues that the way a company organizes itself or its management is directly related to the need for technologies. For Galbraith (1974), typically, companies have two alternative strategies to compete in an environment of uncertainty and increased information needs: 1) develop product inventories to reduce the effect of uncertainty and; 2) implement structural mechanisms and information processing capabilities to enhance the flow of information and reduce uncertainty.

Thus, in an environment of uncertainty and need for information processing, the use of BDA, the company increases the ability to use information in decision making and execution of activities. In this case, it may involve investments in complementary technologies, including the improvement of existing information processing. As the functionality of BDA increases, upgrades to more complex systems are quickly needed (MULLER; JENSEN, 2017).

The investments in information technologies and systems help companies deal with their increasingly complex information needs. While many companies have used it to extract new insights and create new forms of value, other companies have yet to use Big Data to streamline their supply chain operations (SANDERS, 2016). It is also expected to result in other benefits (MIKALEF *et al*., 2019), including increased productivity, improved quality, and facilitation for interorganizational alliances.

Thus it is to be assumed that:

H_6: There is a positive relationship between BDA and logistics operational performance

2.3 The mediating effect of ADB on the relationship between strategic logistics management and logistics operational performance

The GELS as a component of supply chain management (CSCMP, 2019), leads to improved DOL, in turn to SC (MENTZER *et al*., 2001; BOWERSOX *et al*., 2014). Also, authors such as Mikalef *et al*. (2019) argue that investments in information and communication technologies in logistics activities leverage DOL, although, other studies show mixed results with arguments that investments in technologies do not necessarily lead to better DOL (FAWCETT *et al*., 2011).

These paradoxical results suggest the clear and concise direct connection of GELS and DOL can be explained by several factors, including the unavailability of appropriate data, delays in investments in information and communication technology, accuracy of the value generated by these investments, and the absence of an assessment of the benefits of the implemented technology (WAMBA *et al*., 2016).

In reality, according to Mooney *et al*. (1996), these controversial results may be mediated by a number of intermediate variables (MOONEY *et al*., 1996). Thus, when it comes to the use of digital technology, BDA or big data analysis, with the appropriate digital statistical treatment, can transform the large volume of data (varied, structured and unstructured) into useful information for companies in defining strategies, including manufacturing, marketing, logistics, coordination of interrelated supply chain activities, in such a way as to add value to customers, reduce costs and generate new demands (BALLOU, 2006; NOVAES, 2015).

Thus it is to be assumed that:

H_7: The BDA mediates the relationship between strategic logistics management in services and logistics operational performance

Therefore, in this case (of mediation), the relationships [GELS $\rightarrow$ BDA] and [BDA $\rightarrow$ SC] should be statistically significant ($\alpha \leq 0.05$).

2.4 Logistics operational performance and customer satisfaction

E-commerce is an online sales process in which customers proactively specify and purchase one or more products from a variety of items marketed by the company (ARORA, 2008). In this sense, the customization of online purchase alone constitutes a differentiation that can generate SC (PORTER, 1985; HU *et al*., 2016). Adds Meidute-Kavaliauskiene *et al*. (2014), CS is important for companies operating in the service logistics industry, whose competitive advantage is manifested primarily in terms of time and place. Put another way, products and services have no value unless they are in customers' possession when (time) and where (place) they intend to consume them (CHRISTOPHER, 1997; BALLOU, 2006).

Mentzer and Williams (2001) argue that online retail companies can increase their competitiveness by making customers satisfied with logistics service. Also, according to Mentzer and Williams (2001), the level of CS can be increased by offering different logistics services based on the distinct priorities of each customer group.

In this sense, Novaes (2015) cites that a factor that is reflected in the company's DOL is the previous experience in this type of activity. Traditional stores, when they decide to operate also in online sales, bring with them all the logistical experience obtained during the years that they operated in a traditional way. This relevant experience usually includes inventory management, purchasing, physical distribution, transportation, and customer service, which gives them a certain advantage in online operations.

Therefore, from the GELS point of view, ecommerce companies can increase online shoppers' expectations by setting DOL goals such as punctuality, flexibility, lower product price, traceability, and technical assistance. According to Parasuraman *et al*. (1988) the high quality of logistics in services strengthens the company's brand by the excellence of services practiced; and online shoppers by realizing the company's DOL meets their expectations, customers will be satisfied with their purchase.

Thus it is to be assumed that:

H_8: Logistical operational performance impacts customer satisfaction

3 METHODOLOGICAL PROCEDURES

3.1 Nature and Type of Research, Instrument for Data Collection, Sample, Sample Size and Subject of Research

The research was considered exploratory in nature of quantitative type. Initially, it was carried out a study for the validation of the measures content (HAIR *et al*., 2014), through in-depth interviews with three managers of e-commerce companies. To this end, a script was developed to serve as a guide for the interviews, which were recorded, transcribed and analyzed in relation to the elements of the GELS, use and analysis of Big Data, DOL and SC.

With the analysis and results of the collected data, a semi-structured questionnaire was developed, composed of two groups (DILLMAN, 2000). The first refers to the demographic data of the respondent (name, address, time in the function, etc.) and of the companies (size, billing, branch of activity, etc.); the second refers to the constructs: a) GELS elements being: pre transaction, with 8 measures; transaction, with 9 measures and; post transaction with 9 measures; b) *Big Data*, with 9 measures; c) DOL, with 8 measures and; d) CS with 9 measures. In this group of measures, the respondent was asked to mark with an 'x' the degree of disagreement or agreement, on a scale of 1 (DT = Strongly Disagree) to 6 (CT = Strongly Agree), in relation to the measure in its respective construct.

Next, pre-tests were carried out with a sample of five managers in ecommerce companies. Thus, it was possible to eliminate and adjust problems related to the lack of clarity of the content of the assertions, the wording, the sequence and the format for a better understanding of the questionnaire. Once the changes suggested in the pre-tests were made, a sample of ecommerce companies that had virtual sales channels, storage and retail, available on the internet, was chosen by accessibility. For data collection, the online tool Google Forms® was utilized to send questionnaires to the research subjects, composed of employees, managers and ecommerce operators of Brazilian companies, especially in the metropolitan region of the municipality of São Paulo, where the vast majority of ecommerce companies are concentrated. It is noteworthy that the sending of the questionnaire was preceded by an email with justifications and instructions on how to fill out the questionnaire, the purpose of the survey and the electronic address (link) to forward the answers.

3.2 Data Treatment

Initially, we sought to validate the measures and scales of the measurement model. To this end, factor analysis was used to examine the latent patterns or relationships due to the large number of variables used and to determine whether the information could be condensed or summarized in a smaller set of factors or components. To this end, the following tests were used: the unidimensionality given by Cronbach's alpha coefficient, whose minimum limit is 0.7 (HAIR *et al*., 2014); composite reliability that has a satisfactory value greater than 0.7 (HAIR *et al*, 2014); content validity performed in the exploratory study and pre-tests; convergent, obtained by observing the average variance extracted (VME) whose value should be greater than 0.5 (FORNELL; LARCKER, 1981) and; discriminant observed by comparing the square roots of the VME values of each construct with the correlations between the constructs. The square roots of the VMEs should be greater than the correlations between the constructs (FORNELL; LARCKER, 1981).

After that, the statistical significance of the structural relations was verified and the measurement model was estimated. To do so, the PLS-PM (Partial Least Squares-Path Modeling) method was used in structural equation modeling. Pearson's coefficient of determination (R2) was used to evaluate the adjustment of the data to the measurement model. According to Cohen (1988), for the area of social and behavioral sciences, R2 = 2% is classified as small effect; R2 = 13% as medium effect, and R2 = 26% as large effect. Another measure used was the overall quality of fit index given by: [$GoF = \sqrt{\overline{VME} * \overline{R^2}}$)] → [Equation 1]. Tenenhaus *et al*. (2005) e Wetzels *et al*. (2009) consider a value of 0.36 to be adequate. Two other indicators of model fit quality were also used: relevance or predictive validity (Q^2) or Stone-Geisser indicator, whose perfect model would have $Q^2 = 1$ (HAIR *et al*., 2014); and effect size (f^2) or Cohen's indicator whose values of 0.2, 0.15, and 0.35 are considered small, medium, and large, respectively (HAIR *et al*., 2014).

To test and typify the mediating effect of the BDA factor on the relationship between GELS and DOL, the variance accounted for (VAF) test given by was used: VAF = [$\frac{\beta 12 \ x \ \beta 23}{(\beta 12 \ x \ \beta 23)+\beta 13}$] → [Equation 2], where β_{12}, β_{23} and β_{13} are the structural coefficients corresponding to the relationships among the constructs [GELS → BDA], [BDA → DOL] e [GELS → DO], respectively. According to Hair *et al*. (2014), for VAF values > 80%, it means total mediation, VAF < 20% means there is no mediation and 20% ≤ VAF ≤ 80% the mediation is partial. SMARTPLS version 3.0 software was used to handle the collected data.

Delimitation of the Study. There were two main delimitations: a) as to scope. Retail ecommerce companies in the auto parts, white goods and electro-electronics segments, located in the metropolitan region of the city of São Paulo, that practiced at least three dimensions of the BDA were considered. Also considered were companies that had e-commerce as part of their business model, holders of large amounts of data, structured or not, and users of an e-commerce platform and; b) as to conception. The study was considered cross-sectional. In this sense, data from the sample of companies in the ecommerce sector were collected only once.

Method Limitation. The limitations were: a) the choice of the sample elements, which was by accessibility and; b) the sample size. According to Hair *et al*. (2014), for a modeling composed of 52 assertions, a minimum of 256 questionnaires would be necessary (5 times the number of assertions); however, 98 questionnaires were obtained, i.e., below the recommended minimum. Therefore, the results obtained should be viewed with reservations.

4 DATA ANALYSIS AND RESULTS

Data were collected in the second half of 2018. Approximately 1,400 questionnaires were sent out. 104 were returned. After an examination of the received questionnaires as completeness, completeness, and inconsistencies of responses, six were discarded, leaving 98 questionnaires suitable for use in the statistical analyses of the collected data.

4.1 Demographic Profile

1) The demographic profile of the sample, in relation to respondents and companies are shown in Charts 1a and 1b.

Chart 1a - Respondents' profile

Elements	%
- Positions	
Owners and commercial director	3,0
Sales assistants	37,0
Others (business analysts, programmers ...)	60,0
- Academic background	
Administrators	19,4
Information technology	18,4
Outros (engenheiros, contadores ...)	62,2
- Time in the position	
Less than 2 years	31,6
Between 2 and 5 years	37,8
More than 5 years	30,6
- Time in the company	
Less than 2 years	48,0
Between 2 and 5 years	35,7
More than 5 years	16,3

Source: Research data

Chart 1b - Company profile

Elements	%
- Lines of Business	
Retail	84,7
Wholesale	7,1
Other (services, self-employed ...)	8,2
- Size (n. of employees)	
Micro and small business	5,1
Medium enterprise	12,2
Large enterprise	82,7
- Geographic location	
Metropolitan region of SP	100
- Turnover	
Less than R$ 90 million	13,3
Between R$ 90 million and R$ 300 million	19,4
Above R$ 300 million	67,3

Source: Research data

It was observed, by Chart 1a, that the sample was basically composed of respondents who are still in the maturation process, manifested by their positions, education, time in the function and time at the company. Still, from Chart 1b, it was verified that the companies in the sample were composed of retail, large (number of employees and revenues) and concentrated in the metropolitan region of São Paulo.

In summary: the data show that the use of BDA is still incipient, in terms of people (little variation in time in function and in the company) and of predominant use in companies of the large e-commerce retail branch.

2) As for the descriptive aspects of the sample of companies, related to the use of the ADB are shown in Chart 2.

Chart 2 - Aspects of using BDA

Aspects	%
- Em In logistics processes	
Storage	9,2
Order processing	8,2
Credit inquiry	6,1
Transportation	2,0
Others (HR, security ...)	74,5
- BDA usage time	
Less than 1 year	66,4

Between 1 and 3 years	11,2
More than 3 years	22,4
- Phase of use of BDA	
Embryonic	74,5
Maturing	19,4
Expert	6,1
- BDA Platform	
Azure (Microsoft)	9,2
Watson (IBM) / AWS (Amazon) / Oracle	3,0
Did not know how to answer	87,8

Source: Research data

It was observed by Chart 2, that the use of ADB is still embryonic, poorly developed in the logistics functions, of which many respondents could not answer the use of ADB in their company. Despite the low percentage of use in warehousing, order processing, and credit consultation, there is a predominance of applications in the HR and security areas.

In summary: The fact that ecommerce companies do not yet make full use of BDA to analyze and integrate information, has as a consequence, low speed in logistics processes, denoting potential work to be done in the company to search for agility in customer service.

For Haddud *et al*., (2017) the immaturity and low dissemination of knowledge regarding the use of technologies such as BDA, IoT (Internet of Things) and Machine Learning can be caused by the scarcity of literature in the field of management, since they are still concentrated in the area of computer science.

4.2 Validation of Measures and Scales

To examine the latent patterns or relationships of the measurement model, the sample was subjected to factor analysis techniques, exploratory and confirmatory, to debug and validate the set of measures in their respective constructs. After several rounds of debugging, a structure consisting of 52 measures was obtained and distributed in the constructs, of first order, called pre-transaction elements with 8 measures, transaction elements with 9 measures, post-transaction elements with 9 measures, BDA with 9 measures, DOL with 8 measures, and SC with 9 measures. Also, a second-order construct was obtained as a combination of the measures of the pre-transaction, transaction, and post-transaction element constructs, called GELS with 26 measures. Charts A in the Appendix and Chart 1 below show the first and second order factor loadings, which ranged from 0.77 to 0.95 (p-value $\leq$ 0.01), and the results of the factor analysis to meet the minimum requirements for reliability and validity.

A descriptive examination, as noted by Chart 1, showed that the mean ranged, from a minimum value of 3.56 to a maximum value of 4.45, on a scale of 1 to 6 points with standard deviation ranging from a minimum value of 1.26 to a maximum value of 1.44. This result, measures with values greater than 3, and low dispersion, tending toward the agree side of the scale, evidenced that the GELS and BDA favored DOL. For the evaluation of the measurement model, it was also observed by Chart 1, that the -Cronbach and composite reliability (CC) were greater than 0.7, denoting that the indicators had acceptable adjustments on the one-factor model (unidimensional) and; that the indicators of latent constructs were consistent in their measurements, denoting the reliability of the construct (HAIR *et al.*, 2014).

As for convergent validity, it was verified that all factor loadings were greater than 0.7 and the average variance extracted (VME) was above 0.5, revealing convergent validity. In assessing discriminant validity according to Fornell and Larcker's (1981) criteria, we observe in Table 1 that the square root of the mean extracted variance (SEM) of each construct, written on the diagonal and in italics, was greater than the values of the correlation coefficients in row and column, indicating discriminant validity.

Table 1 - Correlation matrix between the first and second order latent variables

CONSTRUCTS	Average	Standard Deviation	Coef. Variation	Correlação bivariada						
				Pre- ransaction	Transaction (operation)	Post-Transaction	G. Estrat. Logitica (2ª Ordem)	Big Data Analytics	Logistic Op. Performance	Client Satisfaction
Pre Transaction	4,21	1,37	0,33	*0,88*						
Transaction (Operation)	4,45	1,44	0,32	0,85	*0,92*					
Post Transaction	4,40	1,42	0,32	0,82	0,91	*0,89*				
G. Strat. Logistic (2nd Order)	4,36	1,35	0,31	0,93	0,97	0,96	*0,85*			
Big Data Analytics	4,33	1,40	0,32	0,73	0,78	0,81	0,81	*0,90*		
Logistic Op. Performance	4,00	1,38	0,35	0,70	0,71	0,75	0,75	0,78	*0,90*	
Client Satisfaction	3,56	1,26	0,35	0,71	0,70	0,73	0,75	0,76	0,91	*0,91*
Cronbach's Alpha (α-Cronbach)			→	0,96	0,98	0,96	0,98	0,97	0,97	0,97
Composite reliability (CC)			→	0,97	0,98	0,97	0,99	0,98	0,97	0,98
Coefficient of Determination (R^2)			→	-	-	-	-	0,66	0,65	0,83
Average extracted variance (AVE)			→	0,78	0,84	0,79	0,73	0,82	0,81	0,83

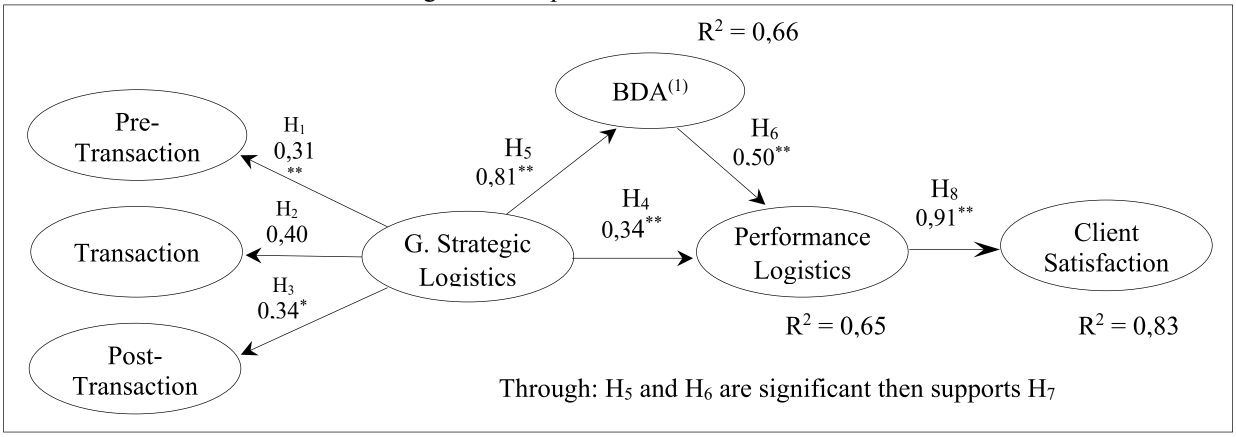
Source: Research data

Table 1 also shows that in the evaluation of the second-order construct, the GELS, the pre-transaction construct (weight = 0.31 and p-value = 0.000), the transaction construct (weight = 0.40 and p-value = 0.001), and the post-transaction construct (weight = 0.34 and p-value = 0.000) contributed to form the GELS construct and that there were reliability (unidimensionality and composite), convergent and discriminant validities at the second-order level.

4.3 Evaluation of the structural relations of the measurement model

To evaluate the statistical significance of relationships and data adjustments to the measurement model, GELS was defined as a 2nd order construct, and was established by repeating the measurements of the 1st order constructs (pre-transaction, transaction and post-transaction elements) that formed it (WETZELS *et al*., 2009). The remaining constructs were considered 1st order, the results of which are shown in Figure 1.

Figure 1 - Empirical-Theoretical Model



Note: [(1)] BDA = Big Data Analytics; The symbol of * indicates that the coefficient is significant at 5%; ** at 1%.
Source: Research data

It was observed from Figure 1, that the coefficient of determination showed a mean value of R^2 equal to 0.71 [(0.66 + 0.65 + 0.83)/3 = 0.71], considered a great effect adjustment. The mean VME was equal to 0.80 [VME = (0.73 + 0.82 + 0.81 + 0.83) / 4 = 0.80], which combined with the R^2, by applying Equation [1], obtained a GoF value equal to 0.75 [GoF = $\sqrt{0.80 * 0.71}$ = 0,75]. GoF value equal to 0.75 indicated above adequate fit. Continuing the analysis of the fits, the indices of predictive validity (Q^2 and sample size effects (f^2) are shown in Table 2.

Table 2 - Predictive Validity (Q^2) and Sample Size Effects (f^2)

CONSTRUCTS	CV RED (Q^2)	CV COM (f^2)
Pre-Transaction	0,66	0,66
Transaction (Operation)	0,66	0,76
Post-Transaction	0,69	0,69
Strategic Logistics Management (2nd Order VL)	0,66	0,66
Big Data Analytics	0,45	0,73
Logistic Operational Performance	0,48	0,72
Customer Satisfaction	0,63	0,74
Reference Values	$Q^2 > 0$	0,02 = pequeno efeito 0,15 = médio efeito 0,35 = grande efeito

CV RED → CV-Redundancy; CV COM → CV-Communality
Source: Research data

The analysis of Table 2 shows that predictive validity (Q^2) showed values greater than zero, indicating that the model was accurate and predictive. As for the effect size (f^2), the values ranged from a minimum of 0.66 to a maximum of 0.76, revealing that the constructs had a large effect on the overall fit of the measurement model.

Therefore, after verifying the consistency of the model fit indices, we proceeded to analyze the statistical significance of the model's structural relations, established by the H_1, H_2, H_3, H_4, H_5, H_6, H_7 and H_8. The results are shown in Table 3.

Table 3 - Structural Coefficients and Hypothesis Test

CONSTRUCTS	STRUCTURAL COEFFICIENT	STANDARD ERROR	VALUE t	HYPOTHESIS	DECISION $\alpha \leq 0,05$
Pre Transaction→ Strategic Logistics Management	0,31	0,01	27,83	H_1	Suporta
Transaction → Strategic Logistics Management	0,40	0,01	32,93	H_2	Suporta
Post Transaction→ Strategic Logistics Management	0,34	0,01	26,68	H_3	Suporta
Strategic Logistics Management → Logistic Dev.- β_{13}	0,34	0,11	3,11	H_4	Suporta
Strategic Logistics Management → BDA - β_{12}	0,81	0,06	13,78	H_5	Suporta
BDA → Logistic Operational Performance - β_{23}	0,50	0,11	4,39	H_6	Suporta
Mediation [H_5 e H_6] are significant (($\alpha \leq 0,05$)	-	-	-	H_7	Suporta
Logistic Operational Performance → Customer Satisfaction	0,91	0,02	50,86	H_8	Suporta

(**) statistically significant for ($\alpha \leq 0.01$) and (*) for ($\alpha \leq 0.05$)

Source: Research data

An examination of Table 3 observed that no hypothesis was rejected, denoting evidence, at the level of significance ($\alpha \leq 0.05$) the consistency of theory with the administrative practices. This result is justified ecommerce logistics as a result of the importance of consumer demands such as speed of delivery and accuracy of documentation, whose first actions are elaborated by GELS to counter consumer impatience (DAUGHERTY, *et al.*, 2018).

Regarding hypothesis H_7, it was also supported (H_5 and H_6 were significant at level $\alpha \leq 0.05$), denoting that the BDA factor acted as a mediator in the relationship between GELS and DOL. In this sense, logistics outsourcing plays a relevant role, especially in the adoption of new management technologies as consumer logistics operations rm which takes into account all sales channels, called omnichannel (RAI *et al.*, 2019).

To verify the typology of the mediating effect of ADB, whether total or partial, the variance accounted test (VAF) was applied, whose values extracted from Table 3 are: $\beta_{12} = 0.81$; $\beta_{23} = 0.50$ and $\beta_{13} = 0,34$. Substituindo these values in Equation [2], we obtained the value VAF = $[\frac{0.81 \, x \, 0.50}{(0.81 \, x \, 0.50)+0.34}] = 0.54$. The value 0.54, according to the approach of Hair *et al.* (2014) is between the range $0.20 \leq VAF \leq 0.80$, so the effect of mediation was considered partial.

5 CONCLUSIONS AND SUGGESTIONS FOR CONTINUATION

The result of the study indicated, at statistical significance level ($\alpha \leq 0.05$), that BDA partially mediates the relationship between GELS and DOL, in turn, impacts SC. This result has the following implications of theoretical and managerial practice nature.

Theoretical implications. The off-line retail market (physical stores), has in logistics services an important influencing component in the level of CS, as shown in the studies of Tucker (1994) and Lalonde and Zinzer (1976), who used the elements of services (pre-transaction, transaction and post-transaction) as influencing the level of CS. Nevertheless, the online market (ecommerce), as in the offline market, also offer logistics services to the consumer, as the sum of all pre-transaction, transaction and post-transaction elements, because consumers react to the total mix, although not all elements of the offered services have the same degree of importance to the consumer.

In this sense, this study examined the elements of logistics services in the online market (e-commerce) with the objective of verifying the role of ADB as a mediating factor in the relationship between GELS and DOL, subsequently the SC. The result showed that BDA mediates, partially, in the relationship between GELS and DOL, which in turn impacts SC, corroborating with the studies of Tucker (1994) and Lalonde and Zinzer (1976). Put another way, BDA is a leverager of GELS to obtain DOL and SC. As a theoretical contribution, it was found that first, the DOL has to be favorable to the firm. From there look for the SC. Obviously, considering DOL as an antecedent variable is implicit in the GELS, nevertheless, we sought to better understand the links between these functions.

Implications for management practices. The online retail (ecommerce) market is growing rapidly which makes competition more exacerbated. To attract new buyers and increase consumer loyalty, online retailers need to make the buyer satisfied with the purchase, not only with the products themselves, but also the delivery service. However, shoppers' requirements are different from person to person. Not only is customization difficult and expensive, but most online retailers outsource the logistics service, which makes direct control over the quality level of the logistics service even more difficult.

But since BDA partially mediates the relationship between GELS and DOL, in turn, impacts SC, online retailers should attach importance to informational data generation (Big Data) and the analysis of that data (Analytics). According to Ittman (2015), the importance of Big Data and the analysis of that data are the two big inevitable trends for logistics managers. Ittmann (2015) further recommends, keeping up to date with these two trends, can help improve the competitiveness of the online retail company.

In fact, only online retailers can increase the level of SC through measures to improve their skills in service logistics quality control, either by building the national logistics network or by establishing joint ventures with service logistics providers. Only when online retailers have the broad mastery of in-service logistics quality control will they be able to offer strategic in-service logistics options to customers (HU *et al*., 2016).

As a contribution to managerial practices, managers of online retail companies, which use logistics services for SC, should benefit from technological advances as well as parallel methodological developments through the analysis of data (BDA) generated by different informational structures and thus become closer to consumers.

Finally, for continuation, it is suggested to increase the sample size of ecommerce companies in the studied economic segment; collect data from other online markets such as food, flowers, etc., or, in other regions of the country; conduct longitudinal research to buy results between periods such as annual or semiannual. Also, to verify if DOL is still an antecedent variable of KS.

Thus, one can improve the understanding of the mediating effect of BDA in the relationship between strategic logistics service management and DOL, in turn, on e-commerce SC.

REFERENCES

ARORA, N.; DREZE, X.; GHOSE, A.; HESS, J. D.; IYENGAR, R.; JING, B.; JOSHI, Y.; KUMAR, V.; LURIE, N.; NESLIN, S.; SAJEESH, S.; SU, M.; SYAM, N.; THOMAS, J.; ZHANG, Z. J. Putting one-to-one marketing to work: personalization, customization and choice. USA, **Marketing Letters**. v. 19, n. 3-4, p. 305-321. 2008.

BALLOU, R. H. **Gerenciamento da cadeia de suprimentos**: planejamento, organização e logística empresarial. 4. ed., Porto Alegre: Bookman, 2006, 616p.

BOWERSOX, D. J.; CLOSS, D. J.; COOPER, M. B.; BOWERSOX, J. C. **Gestão logística da cadeia de suprimentos**. 4. ed. Porto Alegre: AMGH, 2014. 455p.

BRAGANÇA. E. **O que é *Omnichannel* e como aplicar ao *e-commerce***. Disponível em: https://blog.freterapido.com/o-que-e-omnichannel-e-como-aplicar-ao-e-commerce/?gclid=CjwKCAjw1_PqBRBIEiwA71rmtZyND7Zff2lo0ub7vuML_zF-o9OxJ7eA0Mk8pPgE1RrRiqvcLAfcaRoCg0IQAvD_BwE. Acesso em: 26 ago. 2019.

CSCMP – Council of Supply Chain Management Professionals. 2019. Retrieved from: https://cscmp.org/CSCMP/Educate/SCM_Definitions_and_Glossary_of_Terms.aspx. Accessed September 10, 2021

CHEN, D. Q.; PRESTON, D. S.; SWINK, M. How the use of big data analytics affects value creation in supply chain management. USA, **Journal of management information systems**. v. 32, n. 4, p. 4-39. 2015.

COHEN, J. **Statistical power analysis for the behavioral sciences**. 2th edition. New York: Psychology Press, 1988.

CHRISTOPHER, M. **Logística e gerenciamento da cadeia de suprimentos**: estratégias para a redução de custos e melhoria dos serviços. São Paulo: Pioneira, 1997. 240p.

DAUGHERTY, P. J.; BOLUMOLE, Y.; GRAWE, S. J. The new age of customer impatience. USA, **International Journal of Psysical Distribution & Logistics Management**. v. 49, n. 1, p. 4-32, 2019.

DILLMAN, D. A. **Mail and internet surveys**: the tailored design method. 2a. edition. USA: John Wiley & Sons, INC., 2000, 464p.

FAWCETT, S. E.; WALLIN, C.; ALLRED, C.; FAWCETT, A. M.; MAGNAN, G. M. Information technology as na enabler of supply chain collaboration: a dynamic-capabilities perspective. USA, **Journal of supply chain management**. v. 47, n. 1, p. 38-59. 2011.

FORNELL, C.; LARCKER, D. F. Evaluating structural equation models with unobservable variables and measurement error. USA, **Journal of Marketing Research**. v. 18, n. 1, p. 39-50. 1981.

FRAZZON, E. M.; TABOADA, C. M.; PEREIRA, M. M.; PIRES, M. C.; UHLMANN, I. Towards supply chain management 4.0. Towards supply chain management 4.0. Rio de Janeiro, **Brazilian Journal of Operations & Production Management**, v. 16, n. 2, p. 180-191, 2019. DOI: https://doi.org/10.14488/BJOPM.2019.v16.n2.a2

GALBRAITH, J. R. Organization design: an information processing view, European Institute of Advanced Studies. **Interfaces**. v. 4, n. 3, may 1974.

GUEDES, F. Primeiras reflexões sobre *Omnichannel*. 2015. Disponível em: https://www.ilos.com.br/web/primeiras-reflexoes-sobre-omni-channel/-16/11/2015/em Blog /. Acesso em: 27 ago 2019.

GUY, S. **Os desafios logísticos e operacionais do varejo omnichannel**. 2015. Disponível em: https://www.ecommercebrasil.com.br/artigos/os-desafios-logisticos-e-operacionais-do-varejo-omnichannel/. Acesso em: 20 ago. 2019.

HADDUD, A.; DeSOUZA, A.; KHARE, A.; LEE, H. Examining potential benefits and challenges associated with the internet of things integration in supply chains. USA, **Journal of Manufacturing Technology Management**, v. 28, n. 8, p. 1055-1085, 2017.

HAIR, J. F.; HULT, G. T.; RINGLE, C. M.; SARSTEDT, M. **A primer on partial least squares structural equation modeling (PLS-SEM).** Los Angeles: Sage Publications. 2014.

HOFMANN, E. Big data and supply chain decisions: the impact of volume, variety and velocity properties on the bullwhip effect. USA, **International Journal of Production Research.** v. 55, n. 17, p**.** 5108-5126. http://dx.doi.org/10.1080/00207543.2015.1061222. 2015.

HU, M.; HUANG, F.; HOU, H.; CHEN, Y.; BULYSHEVA, L. Customized logistics service and online shoppers' satisfaction: an empirical study. USA, **Internet Research**, v. 26, n. 2, p. 484-497, 2016.

ITTMANN, H. W. The impact of big data and business analytics on supply chain management. USA, **Journal of Transport and Supply Chain Management**. v. 9, n. 1, p. 1-9, 2015.

LALONDE, B. J.; ZINZER, P. H. **Customer services**: meaning and measurement. Chicago: National Council of Physical Distribution Management, 1976.

LIM, S. F. W. T.; SRAI, J. S. Examining the anatomy of last-mile distribution in ecommerce omnichannel retailing. A supply network configuration approach. USA, **International Journal of Operations & Production Management**. v. 38, n. 9, p. 1735-1764, 2018. DOI https://doi.org/10.1108/IJOPM-12-2016-0733.

LOVELOCK, C. H. Classifying services to gain strategic marketing insights. USA**, Journal of Marketing**. v. 47, p. 9-20, 1983.

MEIDUTE-KAVALAUSKIENE, I.; ARANSKIS, A.; LITVINENKO, M. USA: **Procedia – social and behavioral sciences**. v. 110, p. 330-340. 2014.

MENTZER, J. T.; DANIEL, J. F.; HULT, T. M. Logistics service quality as a segment-customized process. USA, **Journal of marketing**. v. 65, p. 82-104. 2001.

MENTZER, J. T.; WILLIAMS, L. R. The role of logistics leverage in marketing strategy. USA, **Journal of Marketing Channels**. v. 8, Issue 3-4, 2001.

MIKALEF, O.; KROGSTIE, J.; PAPPAS, I. O.; PAVLOU, P. **Exploring the relationship between big data analytics capability and competitive performance:** the medating roles of dynamic and operational capabilities. USA: Informations & Management. 2019.

MILLER, L. Casas Bahia e Ponto Frio lançam sua versão dos Amazon Locker no Brasil. 2018. Disponível em: https://www.tecmundo.com.br/internet/126098-casas-bahia-ponto-frio-lancam-versao-amazon-locker-brasil.htm. Acesso em: 25 ago. 2019.

MOONEY, J. G.; GURBAXANI, V.; KRAEMER, K. L. A process oriented framework for assessing the business value of information technology. SIGMIS Database, v. 27, n. 2, p. 68-81. 1996. https://doi.org/10.1145/243350.243363.

MULLER, S. D.; JENSEN, P. Big data in the Danish industry: application and value creation. **Business process management journal**. v. 23, n. 3, p. 645-670. 2017.

NOVAES, A. G. **Logística e gerenciamento da cadeia de distribuição**: estratégia, operação e avaliação. 4. ed. Rio de Janeiro: Elsevier, 2015.

PARASURAMAN, A.; ZEITHAML, V. A.; BERRY, L. L. SERVQUAL: a multiple-item scale for measuring customer perceptions of service quality. USA, **Journal of Retailing**. v. 64, n. 1, p. 12-40. 1988.

PORTER, M. E. **Competitive advantage**. New York. The Free Press, 1985.

PORTER, M. E.; HEPPELMANN, J. E. **How smart, connected products are**

transforming companies. USA: Harvard Business Review. October, 2015.

RAI, H. B.; VERLINDE, S.; MACHARIS, C.; SCHOUTTEED, P.; VANHAVERBEKE, L. Logistics outsourcing in omnichannel retail. USA, **International Journal of Psysical Distribution & Logistics Management**. v. 49, n. 3, p. 267-286, 2019.

SANDERS, N. R. How to use big data to drive your supply chain. USA: University of california, **Berkeley**. v. 58, n. 3. p. 26-48. 2016.

TENENHAUS, M.; VINZI, V. E.; CHATELIN, Y.; LAURO, C. PLS Path Modeling. Computational Statistics & Data Analysis, v.48, p.159-205, 2005.

TUCKER, Francis G. Creative customer service management. USA, **International Journal of Physical Distribution & Logistics Management**. v. 24, n. 4, p. 32-40, 1994.

WAMBA; S. F.; GUNASEKARAN, A.; SHAHRIAR, A.; REN, S. J.; DUBEY, E.; CHILDE, S. Big data analytics and firm performance. USA, **Journal of Business Research**. v. 70, p. 356-365, 2016.

WETZELS, M.; ODEKERKEN-SCHRÖDER, G.; OPPEN, C. V. Using PLS path modeling for assessing hierarchical construct models. USA, **MIS Quarterly**, v. 33, n. 1, p. 177-195. 2009.

WHITTINGTON, R. **O que é estratégia?** São Paulo: International Thomson Editores, 2002. 179p.

WILLIAMSON, O. E. **Transaction cost economics: the precursors**. USA: Institute of Economic Affairs 2008. Published by Blackwell Publishing, Oxford. 2008.

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APPENDIX - Table A: 2nd and 1st order load factors of the measurement model

CONSTRUCT / MESUREMENTS		Load Order						
		2ª	1ª					
		GELS	BDA	DO	PosTr	PreTr	SC	TrOp
STRATEGIC MANAGEMENT OF SERVICE	**Pre-Transaction Reflective Indicators**							
	PR1 Formally establish customer service policy	0,77	0,54	0,63	0,68	**0,85**	0,63	0,68
	PR2 Define service level for customers	0,79	0,62	0,58	0,71	**0,89**	0,58	0,69
	PR3 Define deadlines for customer delivery	0,86	0,73	0,60	0,75	**0,89**	0,63	0,81
	PR4 Elaborate contingency plans	0,83	0,66	0,63	0,70	**0,91**	0,61	0,78
	PR5 Provide accessibility of company information to the customer	0,83	0,63	0,63	0,73	**0,89**	0,65	0,75

	PR6 Define the capacity to meet special requests	0,82	0,66	0,59	0,71	**0,90**	0,63	0,75
	PR7 Elaborate customer service manuals	0,80	0,62	0,64	0,70	**0,87**	0,62	0,73
	PR8 Adjust the knowledge of the product to the customer	0,84	0,70	0,60	0,78	**0,85**	0,65	0,78
	Reflective Indicators Transaction (operation)							
	TR1 Control stock-out level	0,86	0,65	0,60	0,78	0,78	0,64	**0,88**
	TR2 Have skills with open orders	0,90	0,68	0,64	0,82	0,83	0,65	**0,91**
	TR3 Know the elements of the order cycle	0,92	0,75	0,70	0,84	0,84	0,69	**0,93**
	TR4 Control delivery time	0,92	0,78	0,69	0,86	0,81	0,68	**0,95**
	TR5 Manage product deliveries	0,92	0,80	0,70	0,87	0,80	0,70	**0,95**
	TR6 Manage received orders and delivered orders	0,90	0,74	0,66	0,86	0,75	0,64	**0,93**
	TR7 Control backorder requests(delay)	0,89	0,71	0,64	0,84	0,76	0,60	**0,93**
	TR8 Manage backorder time(delay)	0,87	0,68	0,63	0,82	0,74	0,59	**0,91**
	TR9 Control delivery of wrong items	0,82	0,64	0,57	0,79	0,69	0,54	**0,84**
	Post Transaction Reflective Indicators							
	PO1 Meet product warranty as specified in PO2 Product acquisition	0,88	0,74	0,65	**0,92**	0,75	0,66	0,84
	PO3 Provide product exchanges due to returns	0,84	0,68	0,64	**0,91**	0,70	0,65	0,80
	PO4 Provide repairs to the returned product	0,81	0,59	0,64	**0,88**	0,68	0,66	0,75
	PO5 Have spare parts for the product available	0,82	0,69	0,61	**0,85**	0,70	0,60	0,80
	PO6 Track the delivered product	0,89	0,78	0,67	**0,88**	0,78	0,64	0,86
	PO7 Meet the demands of customer complaints	0,89	0,79	0,68	**0,94**	0,77	0,67	0,84
	PO8 Respond quickly to customer complaints	0,86	0,76	0,69	**0,89**	0,74	0,66	0,82
	PO9 Pack the returned product properly	0,78	0,68	0,69	**0,81**	0,68	0,62	0,73
BIG DATA ANALYTICS (1st Order)	BD1 Allows you to analyze the purchase expenses	-	**0,92**	0,77	0,83	0,78	0,77	0,83
	BD2 Allows you to analyze the customer's history	-	**0,91**	0,71	0,77	0,64	0,68	0,74
	BD3 Allows to optimize the supply chain	-	**0,95**	0,71	0,78	0,70	0,70	0,75
	BD4 Allows you to improve warehouse operations	-	**0,95**	0,71	0,72	0,68	0,69	0,73
	BD5 Allows you to monitor processes	-	**0,93**	0,73	0,71	0,65	0,71	0,70
	BD6 Allows you to detail sales reports in hierarchical level	-	**0,86**	0,72	0,71	0,64	0,68	0,63
	BD7 Allows to have volume data to aid decisions	-	**0,92**	0,68	0,74	0,67	0,67	0,72
	BD8 Allows the customer to track order deliveries	-	**0,88**	0,64	0,66	0,59	0,63	0,62
	BD9 Allows to announce products of the customer's preference	-	**0,83**	0,67	0,64	0,60	0,68	0,61
OPERATIONAL DEV. (1st Order)	DO1 Improved the accuracy of shipped orders	-	0,72	**0,85**	0,72	0,70	0,74	0,72
	DO2 Reduced the average order cycle time	-	0,71	**0,88**	0,74	0,75	0,77	0,73
	DO3 Improved on-time delivery of product to customer	-	0,68	**0,92**	0,71	0,66	0,82	0,64
	DO4 Increased delivery flexibility rate	-	0,68	**0,93**	0,64	0,62	0,86	0,59
	DO5 Reduced the failure rates due to logistics management	-	0,70	**0,92**	0,63	0,57	0,87	0,61
	DO6 Reduced product recovery rates	-	0,71	**0,93**	0,63	0,56	0,84	0,61
	DO7 Reduced return rates	-	0,70	**0,89**	0,60	0,54	0,80	0,57
	DO8 Increased delivery frequency	-	0,72	**0,88**	0,70	0,61	0,83	0,63
CUSTOMER SAT. (1st Order)	SC1 Improved customer return rate for e-commerce	-	0,70	0,80	0,68	0,60	**0,90**	0,62
	SC2 Increased the number of recommendations to friends	-	0,68	0,86	0,63	0,63	**0,94**	0,59
	SC3 Improved the image of the delivery service	-	0,64	0,84	0,64	0,62	**0,93**	0,62
	SC4 Improved the online shopping page	-	0,63	0,71	0,71	0,68	**0,81**	0,66
	SC5 Improved complaint handling	-	0,72	0,81	0,65	0,65	**0,93**	0,67
	SC6 Increased the number of warnings for delivery delays	-	0,66	0,83	0,59	0,59	**0,92**	0,61
	SC7 Increased the number of surveys to align with the customer	-	0,73	0,86	0,64	0,64	**0,93**	0,66
	SC8 Improved warranty notifications in case of failures	-	0,74	0,89	0,71	0,72	**0,93**	0,67
	SC9 Improved satisfaction with the physical integrity of the product	-	0,75	0,86	0,73	0,70	**0,91**	0,65

Source: Research Data