PMKT
BRAZILIAN JOURNAL OF MARKETING, OPINION, AND MEDIA RESEARCH

Chief Editor: Fauze Najib Mattar | Associate Editor: Claudio Alberto de Moraes
Evaluation System: Triple Blind Review
Published by: ABEP - Brazilian Association of Research Companies
Languages: Portuguese and English | ISSN: 2317-0123 (online)

New model of customer satisfaction for the power distribution sector in Portugal

Novo modelo de satisfação do cliente para o setor da distribuição de energia em Portugal

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ABSTRACT

This work proposes an explanatory model based on the ECSI Portugal model, adapted to the energy distribution sector in Portugal The analysis of the measurement and structural submodels was performed, and the relationships between the antecedent latent variables: image, empathy, perceived quality and value, with the central variable satisfaction and the consequent latent variables: complaints and loyalty. The model fulfilled the assumptions of establishing the impacts on measurable and latent variables and generated indices comparable to the ECSI Portugal model. It was verified that the perception of customers in fundamental dimensions such as quality, loyalty, complaints and satisfaction was superior to the values obtained with the ECSI Portugal model. Dimensions such as value and empathy exhibited neutral perception and image achieved a perception inferior to that obtained with the ECSI Portugal model. It was found that quality of service has a significant impact on satisfaction and this has a significant impact on loyalty and complaints. The application of the model allows the company to direct its attention to indicators with values of impact below expectations and on which variables its attention should be a priority.

KEYWORDS: Explanatory models; Latent variables; Structural equation models; PLS.

RESUMO

Neste artigo é proposto um modelo explicativo baseado no modelo ECSI Portugal, adaptado ao setor da distribuição de energia em Portugal. A análise dos submodelos de medida e estrutural foi realizada, tendo sido exploradas as relações entre as variáveis latentes antecedentes: imagem, empatia, qualidade percebida e valor, com a variável central satisfação e as variáveis latentes consequentes: reclamações e lealdade. O modelo cumpriu os pressupostos de estabelecer os impactos sobre as varáveis de medida e latentes e gerar índices comparáveis com o modelo ECSI Portugal. Verificou-se que a percepção dos clientes sobre a qualidade, a lealdade, as reclamações e a satisfação, foi superior aos valores obtidos com o modelo ECSI Portugal. Dimensões como o valor e a empatia exibiram percepção neutra e a imagem percepção inferior relativamente à obtida com o modelo ECSI Portugal. Constatou-se que a qualidade de serviço tem um impacto significativo na satisfação e esta tem um impacto significativo na lealdade e nas reclamações. A aplicação do modelo permite que a empresa dê a devida atenção aos indicadores com valores de impacto abaixo do esperado e sobre quais variáveis deve ter atenção prioritária.

PALAVRAS-CHAVE: Modelos explicativos; Variáveis latentes; Modelos de equações estruturais; PLS.

Submission: 30 January 2017
Approval: 13 March 2017

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1 INTRODUCTION

The National Consumer Satisfaction Index in Portugal (ECSI Portugal) is a system for measuring the quality of goods and services available in the national market, through customer satisfaction. ECSI Portugal integrates customer satisfaction as a central objective in the management of organizations, providing them with instruments of action in this field; provides organizations a framework for communication between their customers, their employees and their shareholders; defends consumers' interests by giving them the opportunity to evaluate and to be heard in quality improvement processes; builds a platform for comparison at the organization, sector of activity and country levels; contributes to competitiveness and economic development (Vilares & Coelho, 2011).

The methodology used in the estimation of the ECSI Portugal Model is structural, probabilistic and of simultaneous estimation in detriment of a descriptive (or non-structural) approach. This second approach consists in the accomplishment of a standard market study with enterprise's customers, from which satisfaction indicators are directly derived. No causal relationship (or from other type) is specified among the different variables under study, thus providing very little information about the nature of the relationships between those variables (Vilares & Coelho, 2011). On the other hand, in the case of a structural approach, the data from the enterprise's customer survey is used to estimate the customer satisfaction model. It is the estimation of this model that provides the satisfaction indices.

The indices obtained through this structural approach possess a set of properties known as performance criteria, and are not usually found in non-structural or descriptive approaches. The main properties are: ability to forecast results, that is, the capability of indices as advanced indicators in relation to performance; diagnostic capability, the ability of the model to explain and quantify the causes for the values of different indices and, in particular, the satisfaction and loyalty indices; possibility of aggregation, that is, the possibility of developing indices for the organization, or segments of customers or employees; comparability, that is, the possibility of comparing indices of different variables, different segments and different brands, allowing benchmarking between them (Vilares & Coelho, 2011). In addition to these advantages, the ability of this approach allows for gains in accuracy over the indicators provided by purely descriptive approaches.

The first nationally calculated customer satisfaction index at the enterprise level appears in 1989 in Sweden and it is known as the Swedish Customer Satisfaction Index (SCSI) with five latent variables. This index had a substantial booster with the researcher Fornell (1992), the main sponsor of the studies developed in the Swedish Post, with 31 industries (Figure 1).

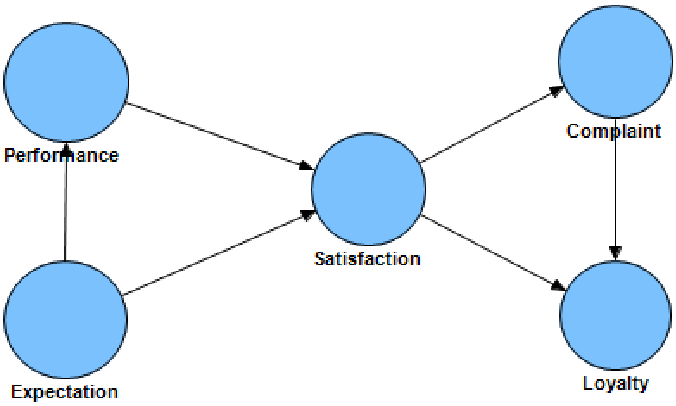

Figure 1 - Swedish Customer Satisfaction Barometer (SCSB)
Source: Johnson, Gustafsson, Andreassen, Lervik, & Cha, 2001.

The American Society for Quality commissioned in 1991 the consulting firm National Economic Research Associates to analyze and advise the best methodology for developing a national quality index. Thus, the American Customer Satisfaction Index (ACSI) model with six latent variables (Figure 2) has been applied to US companies with great success.

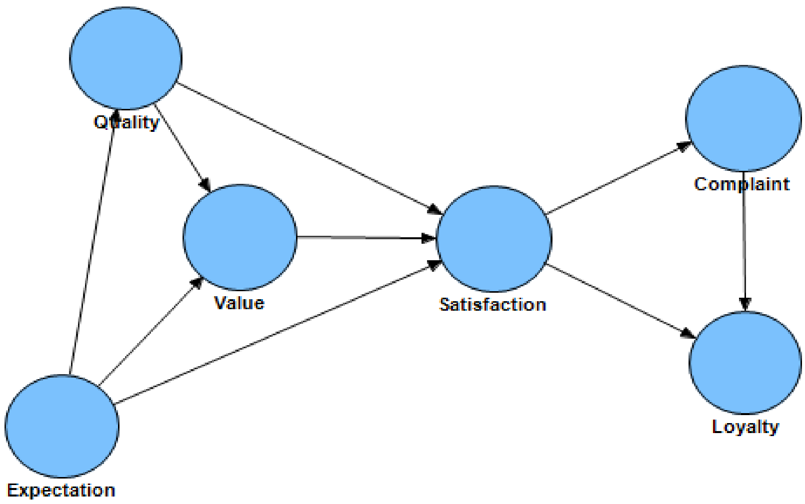

Figure 2 - American Customer Satisfaction Index (ACSI)
Source: Vilares and Coelho, 2011.

The European Customer Satisfaction Index (ECSI) differs from the ASCI model by the insertion of a new latent variable, the image, and the withdrawing of the variable complaints, keeping the model six latent variables (Figure 3).

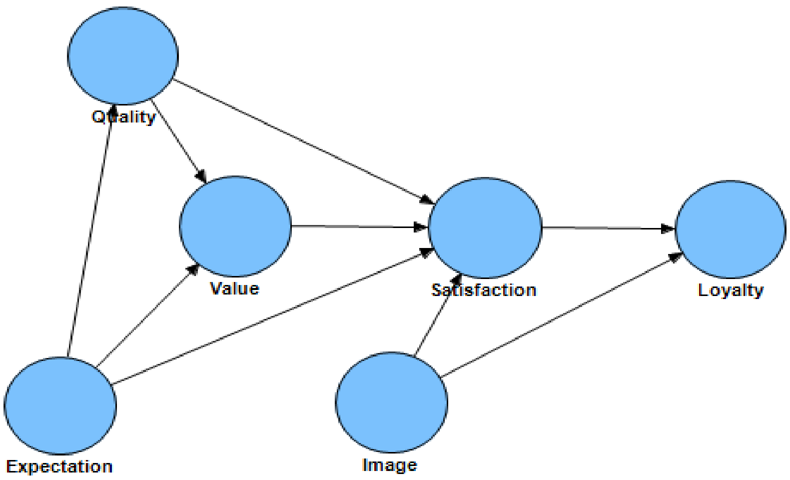

Figure 3 - European Customer Satisfaction Index (ECSI)
Source: Adapted from Johnson *et al.*, 2001.

In the ECSI Portugal model, the complaints dimension is reintroduced, the latent variables become seven, and the relationships are changed, as it can be observed in figure 4 where the basic structure of the model is presented schematically.

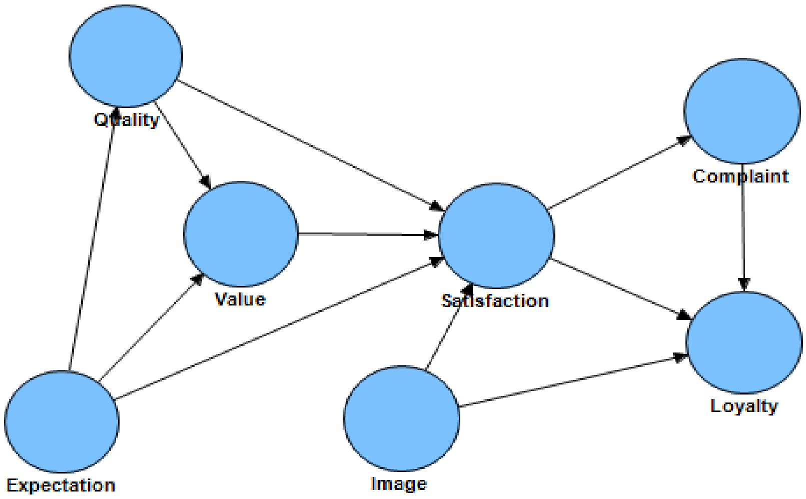

Figure 4 - Basic Structure of the ECSI Portugal model
Source: Vilares and Coelho, 2005.

The customer satisfaction index is explained by four determinants or antecedents: image, customer expectations, perceived quality and perceived value or price/quality ratio.

In the present work one intends to evaluate the satisfaction of residential customers of EDP Distribution using a new proposed model, and to compare the results with those obtained by ESCI Portugal 2012.

In this paper, a new model is proposed, called the ISCFEE model (Satisfaction Index with the Supply of Electric Energy). It is a model similar to the ECSI Portugal satisfaction model, with a modification: the replacement of the expectations dimension by the empathy dimension. This change was made based on the experience and sensitivity of EDP Distribution workers, who observed that empathy is strongly correlated with expectations and could influence more substantially the dimensions perceived value and quality. The model is composed of seven latent variables, evaluated through items from a questionnaire on a scale from 1 to 10, where the value 1 represents a very negative perception and 10 a very positive perception, by the client. The elaboration of an alternative model adapted to a company that provides a service with very specific characteristics was the path followed herein. Figure 5 shows the ISCFEE model.

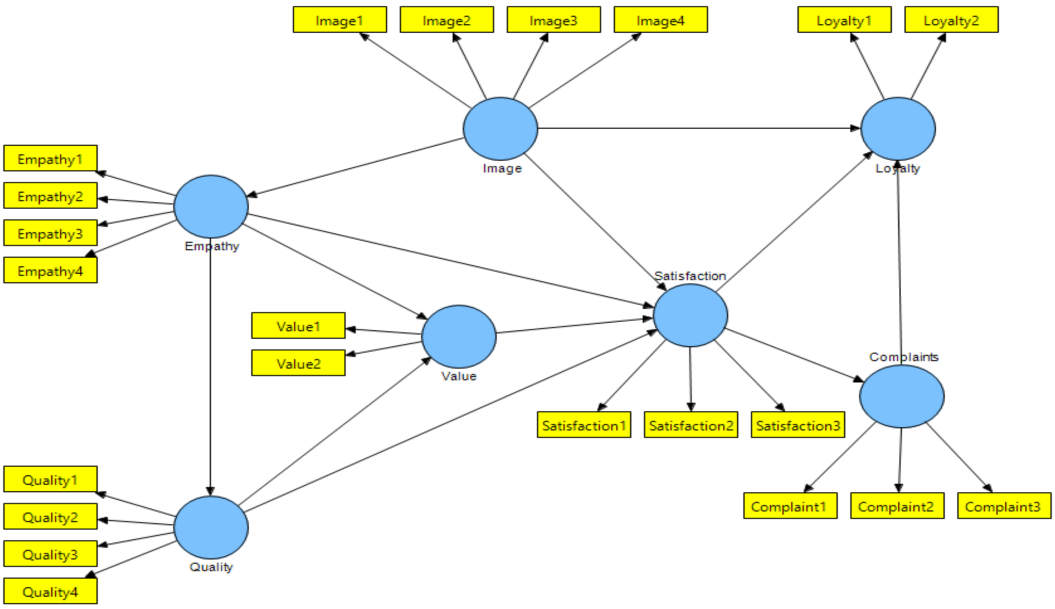

Figure 5 –ISCFEE Model
Source: Scheme developed with the support of the software SmartPLS.

The model contains a single exogenous variable, the image, and six endogenous variables. As in the ECSI model, customer satisfaction is the central variable of the model. It has as antecedents the image of the company, the empathy with it, the perceived quality of the service and the perceived value. The consequences of customer satisfaction are loyalty to the company and the perception of how the company handles customer complaints.

2 REVIEW OF THE LITERATURE

Structural equation models comprise the analysis of two conceptually distinct submodels. The measurement (outer) model, which specifies the relationship between the manifest variables and the hypothetical latent variables, and the structural (inner) model, which specifies the causal relationships between the latent variables.

The two most common procedures for applying this type of model are the analysis of covariance-based structural equation models, the CB-SEM (Jöreskog, 1970, 1973; Keesling, 1972; Wiley, 1973) and the analysis of the path models by the partial least squares method, PLS-SEM (Wold, 1980, 1981).

The CB-SEM is characterized by allowing complex causal relationships between the latent variables and gives particular emphasis to the global adjustment of covariance matrices, hence its importance in confirmatory analyzes. It assumes multivariate normality of data and large samples. Alternative estimation methods for maximum likelihood allow the analysis of data that do not meet the requirement of the normal multivariate distribution and missing values estimation methods based on the model allow to deal with missing completely at random (MCAR) or missing at random (MAR) data.

PLS-SEM is an alternative method of structural equation analysis that applies the ordinary least squares method to each equation of the structural model. The objective of PLS-SEM is to maximize the variance explained by the endogenous variables, minimizing the residuals (either from the measurement model or from the structural model), which is more appropriate in predictive analyzes and when the sample is small (Hsu, Chen, & Hsieh, 2006), and in exploratory analyzes. PLS-SEM is less affected by data distribution and, although the samples may be smaller, it should always take into account the number of latent variables in the model. Few indicator variables (one or two) can be used for each latent variable in the measurement model or, conversely, include a large number of indicator variables. It assumes that all measured variance is useful for explaining structural relationships (Hair, Hult, Ringle, & Sarstedt, 2013). It is a robust model to the presence of noise and missing values. With regard to the measurement model, PLS-SEM allows the use of latent reflective and latent formative variables, unlike CB-SEM, which only allows the use of latent reflective variables.

The reflective models assume that the latent variable is the reality in which the manifest variables are no more than the reflection of this reality, as opposed to the formative models. They present the disadvantage of greater difficulty in interpreting the factorial weights of the predictors, which are based on cross-association with the dependent variables and not on the covariances or correlations between the manifested variables as in CB-SEM. It has also the disadvantage of lack of knowledge of the estimators' distribution, forcing the significance assessment to be made through simulation.

In the present study the approach adopted was that of the PLS-SEM. This choice for PLS-SEM was essentially due to the fact that it is less restrictive in terms of assumptions, the ordinal nature of the indicators, the objectives essentially predictive of the study and the data violation of the multivariate normality assumption.

2.1 MEASUREMENT MODEL

The formulation of the measurement model depends on the relationships between the latent variables and the corresponding manifest variables.

In a reflective model, each indicator is related to the corresponding latent variable by the linear regression model:

$$x_i = \lambda_{i0} + \lambda_{ik}\xi_k + \epsilon_{ik}, \qquad i = 1, \dots, n_k, \qquad k = 1, \dots, J$$

Being λ_{ik} the *loading* associated with the i-th manifest variable and k-th latent variable, and ϵ_{ik} the specification error (uncorrelated errors). Standardized loadings are usually used (disappearing the constant λ_{i0}) representing the correlations between the manifest variables and the corresponding latent variables. This model assumes the assumption (predictor specification) that the errors have zero mean and are uncorrelated with the corresponding latent variable:

$$E(x_i|\xi_k) = \lambda_{i0} + \lambda_{ik}\xi_k$$

In a formative model:

$$\xi_k = \sum_{i=1}^{n_k} \omega_{ik} x_i + \delta_k$$

Being ω_{ik} the coefficient of the manifest variable x_{ik} in the formative construct, and δ_k represents the fraction of the latent variable not explained by the manifest variables, specification error. In this case, the assumption of the predictor specification is also assumed.

Whatever the type of measurement model, the standardized scores of the latent variables $\hat{\xi}_k$ are computed as linear combination of the corresponding manifest variables:

$$\hat{\xi}_k = \sum_{i=1}^{n_k} w_{ik} x_i$$

Being the manifest variables x_i centered and w_{ik} the weights of the measurement model.

2.2 STRUCTURAL MODEL

The formulation of the structural model is given by the following general equation:

$$\xi_j = \beta_{0j} + \sum_{q:\xi_q \to \xi_j} \beta_{qj}\xi_q + \zeta_j, \qquad j = 1, \dots, J_1, \qquad q = 1, \dots, J$$

Being J the number of latent variables, $J_1 < J$ the number of endogenous latent variables, ξ_j the j-th endogenous latent variable, β_{qj} the path coefficient that links the q-th latent variable with the j-th endogenous latent variable, and ζ_j the specification errors, with mean zero, constant variance and non-correlated with each other.

3 METHODOLOGY

The data were collected by means of a questionnaire. The questionnaire was similar to that used in the ECSI model with the necessary adaptations for the present study. It was validated by a preliminary evaluation of specialists in the area and by means of a pre-test applied to 10 clients of EDP Distribution.

3.1 SAMPLE SELECTION

The target population is made up of all residential customers of EPD Distribution. In the sample, the number of variables to be measured, the heterogeneity of the portuguese population (urban/rural, age, qualifications) and the necessity for representativeness of the population were considered.

The selection of the sample was made from a set of sample units, the so-called survey database, which was defined as covering all inhabitants with fixed telephone number listed on the web pages http://www.pbi.pai.pt/, between September 23 and October 4, 2013. A stratified sampling process by district was followed (continental Portugal has 18 districts).

All selected numbers corresponding to companies or institutions were excluded. The first number selected for the sample corresponds to the first valid contact of the records of the respective district. Periods of 10 numbers were considered for the following records. The average success rate of contacts was 37%. The contact sheets were elaborated and the *call center* operators were trained.

Data collection was accomplished between October 15 and November 29. In the districts of Beja, Bragança, Faro, Guarda, Portalegre, Porto, Viana do Castelo and Vila Real, almost all located in the interior of the country, contact success rates were below average, particularly in the district of Faro. This may be due to the fact that many are holiday homes.

A total of 1146 contacts were performed, and 425 responses were obtained in total. After data collection, 30 quality control calls properly stratified were performed by supervisors (Figure 7), with the objective to confirm the effective accomplishment of the questionnaires. In three cases, of contacts made more than 5 weeks ago, it was not possible to obtain an unequivocal confirmation of their realization, since people no longer remembered. This number is not significant, and the questionnaires were considered valid.

3.2 PRELIMINARY DATA ANALYSIS

The obtained data were initially explored in order to detect situations requiring previous corrections to the statistical procedures, such as missing data, variables with reduced variability or outliers. A variable does not provide valid information for the model if there are insufficient observations or reduced variability. Likewise, the information contained in a case with several missing values can be reduced. For this reason, these variables and/or cases are often removed from the database. This may influence the results of the statistical analysis, so it must be analyzed the best way to treat those cases.

The way of dealing with missing data depends on the quantity, type, and the reason for the missing data. To eliminate cases with missing variables can have several consequences, such as to reduce the sample size and representativeness, to increase associated standard errors, to reduce power (increasing type II error), to lead to biases in estimates and to compromise the external validity of the study. This way, it is of vital importance to inspect the data before making a decision. As an alternative procedure, one may estimate the missing values.

To make a decision on how to handle missing data it becomes necessary to know what kind of data is missing, whether random or not. Rubin (1976) and Little and Rubin (1987) identified three distinct patterns of missing data: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). Missing values cannot be ignored when missing values are not MAR or MCAR, that is, when the probability of missing values cannot be predicted by model variables. If the missing values are at least MAR, they may be deleted or estimated.

In the present study, no evidence of missing MNAR data was observed. The decision was made between deleting or estimating the missing values. The deletion of cases with missing values, listwise deletion, would significantly reduce the sample size, a reduction from 425 cases to 202 would be observed, a significant reduction of about 52.47% of the cases. This way, this approach was discarded. Reviewing the cases and variables with missing values, no variable exhibited more than 20% of missing values. The same did not happen with the cases, in which 20 cases exhibited more than 30%

of missing values. After careful analysis of these cases it was decided to exclude them. For the remaining cases, the estimation was the process employed.

Meaning imputation may reduce the variance of the data. In structural equation models, methods based on the model can be applied. The full information maximum likelihood (FIML) and expectation maximization (MS) estimation methods, based on the classical maximum likelihood algorithm, have been frequently used strategies (Enders, 2001). In the present study, since one is dealing with ordinal variables in which symmetry is not always present, the *k*-nearest neighbor imputation for missing data was chosen to identify and fill in the missing values, by a process of recognizing the 20 most similar cases. This way, all cases can be used and no information is lost.

Knowing that the presence of outliers can affect the results of the statistical analysis to be performed, a procedure implemented in SPSS was used to detect multivariate outliers. This procedure creates a clusters model and some indices for each case to identify how much a case is unusual with respect to its cluster. As this process may depend on the order of cases, several solutions were obtained with different ordering, and the anomaly indices and the impact of each case on the variables that most contribute to the classification of each case as unusual, were compared. In the end, no cases were eliminated.

4 ANALYSIS OF ISCFEE MODEL

In order to evaluate the predictive power of the proposed theoretical model, PLS-SEM was used having one resorted on Smart-PLS software (Ringle, 2005). The two submodels were analyzed: reliability and validity of the measurement model and analysis of the hypothetical relations of the structural model.

4.1 ANALYSIS OF THE MEASUREMENT MODEL

The measurement model represents the relationship between latent variables and their indicators. Since the indicators of the same reflective latent variable measure the same underlying concept, they must be homogeneous and unidimensional.

Cronbach's alpha allows evaluating the homogeneity and unidimensionality of the latent variables, being, therefore, an indicator of the convergent validity and reliability of the constructs. Values greater than 0.9 are regarded as excellent, greater than 0.8 as good, greater than 0.7 as acceptable, greater than 0.6 as weak, and less than 0.6 as unacceptable. The Crohnbach's alpha assumes equal importance for all manifest variables in the formation of the constructs, based on the observed correlations between the manifest variables.

A more powerful alternative to measure reliability and convergent validity is given by the composite reliability or Dillon-Goldstein rho index (Wertz, Linn, & Jöreskog, 1974), which is based on the loadings obtained by the model. The values should be higher than 0.708 for confirmatory purposes (Hair, Anderson, Tatham, & Black, 1998, Hair et al., 2013). Cronbach's alpha more often underestimates the true value of reliability (Vinzi, Trinchera, & Amato, 2010; Chin, 1998). The values obtained for these two indices show good internal reliability, with all values above 0.855 for the composite reliability index. Crohnbach's alpha presents a weak value for the dimension Value (0.660), but considering that this dimension is measured by only two indicators, the result is acceptable (Table 1).

Table 1 - Composite reliability and Cronbach's Alpha

	Composite reliability	Cronbach's alpha
Empathy	0.914	0.875
Image	0.898	0.849
Loyalty	0.927	0.843
Quality	0.904	0.858
Complaint	0.914	0.859
Satisfaction	0.881	0.797
Value	0.855	0.660

The reliability of the items individually is evaluated by examining the loadings, which is, for standardized variables, the simple correlations of the indicators with the respective latent variables of the measurement model. As a rule of thumb, proposed by Carmines and Zeller (1979), the loadings of the measurement model must be at least 0.708, so that the corresponding indicator is accepted as a component of the latent variable and not eliminated. This value reveals a shared variance between the indicator and the construct of at least 50%, which implies that it is greater than the error variance. However, values of at least 0.5 (25% of the indicator variance associated with the construct) may be acceptable if other indicators measuring the same construct display high reliable values (Barclay, Thompson, & Higgins, 1995). Table 2 displays the loadings (in bold) associated with its construct. It turns out that all values are well above 0.708, ranging from 0.772 for the Image1 indicator of Image and 0.937 for the Leal1 indicator of Loyalty.

Table 2 - Loadings

	Empathy	Image	Loyalty	Quality	Complaint	Satisfaction	Value
Empathy1	**0.865**	0.401	-0.091	0.249	0.252	0.215	0.370
Empathy2	**0.876**	0.361	-0.088	0.242	0.244	0.177	0.390
Empathy3	**0.854**	0.468	0.045	0.332	0.373	0.263	0.381
Empathy4	**0.816**	0.353	0.035	0.195	0.321	0.170	0.404
Image1	0.317	**0.772**	0.256	0.449	0.358	0.325	0.408
Image2	0.344	**0.820**	0.189	0.499	0.281	0.402	0.304
Image3	0.451	**0.851**	0.190	0.550	0.351	0.452	0.287
Image4	0.426	**0.873**	0.256	0.545	0.370	0.384	0.298
Loyalty1	0.028	0.274	**0.937**	0.380	0.324	0.490	0.072
Loyalty2	-0.082	0.218	**0.923**	0.318	0.332	0.451	0.074
Quality1	0.376	0.691	0.338	**0.782**	0.535	0.623	0.240
Quality2	0.279	0.493	0.246	**0.812**	0.523	0.563	0.179
Quality3	0.222	0.481	0.302	**0.883**	0.572	0.654	0.307
Quality4	0.146	0.409	0.367	**0.874**	0.587	0.762	0.167
Complaint1	0.322	0.327	0.218	0.561	**0.884**	0.672	0.281
Complaint2	0.366	0.386	0.334	0.559	**0.848**	0.573	0.411
Complaint3	0.258	0.375	0.377	0.631	**0.917**	0.689	0.232
Satisfaction1	0.137	0.413	0.441	0.609	0.611	**0.830**	0.316
Satisfaction2	0.223	0.363	0.435	0.730	0.602	**0.868**	0.204
Satisfaction3	0.259	0.425	0.408	0.633	0.641	**0.833**	0.115
Value1	0.479	0.310	0.001	0.128	0.227	0.111	**0.858**
Value2	0.305	0.353	0.132	0.330	0.362	0.317	**0.870**

Como suporte à validade convergente e validade discriminante, analisaram-se outros índices. Assim, define-se a comunalidade para a q-ésima variável latente ou construto, como sendo a percentagem de variância dos indicadores explicada pela variável latente, ou seja, representa a média das comunalidades de cada indicador (Vinzi et al., 2010):

By examining the crossloadings, none of the indicators presented as problematic, since none has higher loadings associated with other constructs than the construct they intend to measure (Table 2). This analysis also supports the discriminant validity of the model. A good model should have high loadings with the construct that they intend to measure and small crossloadings.

As support for convergent validity and discriminant validity, other indices were analyzed. Thus, the communality is defined for the q-th latent or construct variable, as the percentage of variance of the indicators explained by the latent variable, that is, represents the average of the communalities of each indicator (Vinzi et al., 2010):

$$Communality_q = \frac{1}{n_q}\sum_{i=1}^{n_q} r^2(x_{iq}, \xi_q)$$

Being $r^2(x_{iq}, \xi_q)$ the square of the correlation between the indicator x_{iq} and the construct ξ_q, that is, the communality between the indicator and the construct.

Another important index that is defined for the q-th latent variable, is called the average variance extracted, AVE. In the standardized case:

$$AVE_q = \frac{\sum_{i=1}^{n_q} \lambda_{iq}^2}{\sum_{i=1}^{n_q} \lambda_{iq}^2 + \sum_{i=1}^{n_q} (1 - \lambda_{iq}^2)}$$

Being λ_{iq} the loading between the indicator i and the construct q. It should be noted that the AVE, in the standardized case, equals the communality of the construct.

These indices allow to evaluate the convergent validity and the reliability of the construct, accepting as a minimum acceptable value for the communality, as support to the convergent validity, a value of 0.5, also applicable to the AVE for standardized variables, since the values are equal (Chin, 1998). Lower values should lead the researcher to rethink the use of the latent variable or the indicators, observing other values such as the composite reliability, the crossloadings and the discriminant validity in aid to a decision making.

All AVE values were well above 0.5, as can be seen in Table 3, which corroborates the values of composite reliability and Cronbach's alpha, as a support for a good convergent validity of the constructs.

Table 3 - Average variance extracted (AVE)

	AVE
Empathy	0.728
Image	0.689
Loyalty	0.864
Quality	0.703
Complaint	0.781
Satisfaction	0.712
Value	0.746

The discriminant validity evaluates the extent to which a construct is different from all other constructs. Fornell and Larcker (1981) suggest, for this purpose, the use of the AVE. The criterion called the Fornell-Lacker criterion is often used. This criterion determines that the square root of the AVE for each construct should be superior to all the correlations between this construct and all the others present in the model, thus verifying, in this way, a superior correlation of each construct with its own indicators. In Table 4, where the square root of the AVE for each construct is at the diagonal, one can observe that the proposed model verifies these requirements, which together with the values obtained by the loadings and crossloadings already described, show a good discriminant validity.

Table 4 - Correlations between the latent variables with the square root of the AVE at the diagonal (in bold)

	Empathy	Image	Loyalty	Quality	Complaint	Satisfaction	Value
Empathy	**0.853**						
Image	0.468	**0.830**					
Loyalty	-0.026	0.266	**0.930**				
Quality	0.303	0.618	0.377	**0.839**			
Complaint	0.353	0.410	0.352	0.662	**0.883**		
Satisfaction	0.245	0.474	0.507	0.781	0.732	**0.844**	
Value	0.452	0.385	0.079	0.267	0.342	0.250	**0.864**

4.2 ANALYSIS OF THE STRUCTURAL MODEL

Having confirmed the reliability and validity of the measurement model, one proceeds to the analysis of the structural model. This analysis involves the relationships between the different constructs and the evaluation of the predictive relevance of the model.

Before this analysis is performed, it is necessary to test the collinearity of the structural model, since the estimation of the structural coefficients is based on the least squares method. To evaluate the collinearity, the values of the VIF were used for each set of predictors associated to the same endogenous latent variable. VIF values above 5 (tolerance below 0.2) are considered as indicators of high multicollinearity. By recourse on the linear regression option of IBM SPSS Statistics software, these coefficients were determined for the following three sets of variables:

- Empathy and quality as value predictors;
- Image, satisfaction and complaint as loyalty predictors;
- Empathy, quality, image and value as satisfaction predictors.

The highest VIF value obtained was 2.336 followed by 2.177, with the remaining values below 2, all values well below 5, which indicate that there are no problems of multicollinearity in the model.

In order to proceed with the evaluation of the structural model, the criteria consisted by assessing the significance of the coefficients, the computation of the determination coefficients R^2 and the cross-validated predictive relevance criterion Q^2.

Since the distribution of the PLS-SEM coefficient estimators are not known, to test the significance of the model, bootstrap or jackknife resampling techniques are used, thus allowing the estimation of standard errors and t statistics for each parameter. The process implemented in SmartPLS is a nonparametric bootstrap procedure, in which a large number of subsamples (bootstrap samples) are randomly taken from the original sample with replacement. The number of bootstrap samples should be at least equal to the number of valid observations in the sample, with 5000 samples being recommended (Hair *et al.*, 2013).

Since the number of bootstrap samples is quite large (5000) the resulting t statistics follow approximately a normal distribution, and the quantiles of the standard normal distribution can be used to determine the critical values. Thus, statistic values greater than 1.65 are significant for $\alpha = 0.10$, greater than 1.96 for $\alpha = 0.05$ and above 2.58 for $\alpha = 0.01$. In the measurement model, all loadings revealed strong significance. In the structural model, the results showed seven significant coefficients for the level of 0.01 and five coefficients not significant for the level of 0.10. Table 5 displays these results.

Table 5 - *t* statistics and coefficients of the structural model

	***t* statistic**	**Coefficient**
Empathy -> Quality	5.649679	0.303103***
Empathy -> Satisfaction	0.057545	-0.002032
Empathy -> Value	8.526143	0,408602***
Image -> Empathy	9.622260	0.468468***
Image -> Loyalty	0.555913	0.037307
Image -> Satisfaction	0.617082	-0.032443
Quality -> Satisfaction	18.293761	0.787223***
Quality -> Value	2.956012	0.143309***
Complaint -> Loyalty	0.619851	-0.045851
Satisfaction -> Loyalty	6.355145	0.523134***
Satisfaction -> Complaint	25.430593	0.731833***
Value -> Satisfaction	1.464998	0.053012

$* \, p < 0.1, \quad ** \, p < 0.05, \quad *** \, p < 0.01$

It is imperative to analyze the importance and impact of the seven significant relationships. The analysis is done in the same way as the least squares standardized linear regression. These coefficients estimate the expected variation in the endogenous construct for each point of variation in the predictor construct.

Both the image, the empathy and the perceived value did not show a significant direct influence on the satisfaction of the residential customers of EDP Distribution, either at the level of statistical significance either at the level of the estimated coefficients values. Only the perceived quality has a direct impact on customer satisfaction, where, for each point of variation in perceived quality, an increase of 0.787 points in satisfaction is expected. Satisfaction shows relevant and significant direct impacts on their consequent constructs, loyalty, and complaint.

Besides these direct effects between the variables it is important to analyze the indirect effects through mediating variables. The sum of direct and indirect effects provides the total effect of one variable on another.

These total effects can be observed in Table 6, and there is now some effect, although not very pronounced, on empathy over satisfaction (0.261).

Table 6 - Total effects

	Empathy	**Loyalty**	**Quality**	**Complaint**	**Satisfaction**	**Value**
Empathy		0.127556***	0.303103***	0.190673***	0.260542***	0.452040***
Image	0.468468***	0.081179	0.141994***	0.065582	0.089613	0.211766***
Loyalty						
Quality		0.389127***		0.581676***	0.794820***	0.143309***
Complaint		-0.045851				
Satisfaction		0.489579***		0.731833***		
Value		0.025954		0.038796	0.053012	

$* \, p < 0.1, \quad ** \, p < 0.05, \quad *** \, p < 0.01$

Significance analysis was performed using bootstrap estimates. However, bootstrap estimates are data-dependent and may not be valid for new data, which means that the p-values cannot be interpreted in the usual way as a probability in the population. The bootstrap estimates p-value relates to the probability, that a result of a different sub-sample, to be collected from the sample data. This means that significant estimates may be insufficient and invalid with respect to the predictive relevance of the model (predictive validity), that is, the estimates obtained for the parameters of the structural model may not be able to predict correctly, from new data of the same population of interest, the endogenous latent variables of the model. It turns out to be necessary to define quality and model validation indices.

The quality of the adjustment is evaluated by the determination coefficients R^2, which measure the percentage of variability of the endogenous variables explained by the exogenous variables, that is, the predictive accuracy of the model (Chin, 1998). This goodness-of-fit index is compatible with the primary objective of the PLS, which is the forecast. Values of 0.75 are considered substantial, of 0.50 moderate and of 0.25 weak (Hair, Ringle, & Sarstedt, 2011). These values should be at least 0.1 (Falk & Miller, 1992).

In order to analyse the predictive relevance of the model, in addition to the the values of the determination coefficients R^2, which evaluate the predictive accuracy, the predictive validity of the model should be evaluated using the Stone-Geiser's Q^2 statistic (Stone, 1974; Geisser, 1975).

A model with predictive relevance can accurately predict the values of the indicators of endogenous constructs of reflective models (Hair et al., 2013). This statistic is usually obtained from the application of a cross-validation algorithm, called blindfolding (Chin, 2010). In this algorithm, portions of the data are omitted and cross-validated with the estimates obtained from the remaining data. The process is repeated successively with a different set of omitted data until all data has been processed.

The Stone-Geiser Q^2 statistic is generally considered to be more informative than the R^2 and the AVE, since it is not affected by the natural bias that occurs when the assessment is made on the same data that was used to estimate the parameters of the model, overcoming the over-adjustment problem that may occur. A $Q^2 > 0$ suggests a model with predictive relevance. The higher the value the greater the predictive relevance. Values of 0.02, 0.15 and 0.35 denote small, medium or large relevance respectively (Hair *et al.*, 2013). On the contrary, a $Q^2 < 0$ suggests a model with weak predictive relevance.

Two approaches to the determination of the Q^2 statistic have been used, cv-communality and cv-redundancy (cross-validated communality and cross-validated redundancy) (Fornell & Cha, 1994; Chin, 2010).

The cv-communality measures the ability of the model to predict the manifest variables from the scores of its latent variables, being an indicator of the quality of the measurement model for each latent variable. It is a kind of cross-validation of the R^2 between the manifest variables and the associated latent variable (Tenenhau, Vinzi, Chatelin, & Lauro, 2005; Duarte & Raposo, 2010).

The cv-redundancy measures the ability of the model to predict the endogenous manifest variables from the exogenous latent variables, being an indicator of the quality of the structural model. It is a kind of cross-validation of R^2 between the manifest variables of an endogenous latent variable and all the manifest variables associated with the latent variables that explain this endogenous variable, using the estimated structural model (Tenenhaus et al., 2005; Duarte & Raposo, 2010).

The values of R^2 obtained ranged from about 0.092 for the perceived quality, very weak effect value, up to 0.612 for satisfaction, moderate effect value (Table 7). This last value represents a satisfactory effect of the model in explaining customer satisfaction of EDP Distribution, that is, the model explains about 61% of customer satisfaction, with 39% of satisfaction explained by other variables not included in the model. In addition to satisfaction, the model only explains in a moderate way the complaints, whose value obtained indicates about 53.6% of variance explained.

Table 7 - R^2, Redundancy and Cross-validation indices

	R²	Redundancy	cv-communality	cv-redundancy
Empathy	0.219462	0.159695	0.534228**	0.153685*
Image			0.684575**	
Loyalty	0.259142	0.223937	0.493850**	0.213767*
Quality	0.091872	0.064610	0.711456**	0.062943
Complaint	0.535580	0.418028	0.763956**	0.415992**
Satisfaction	0.611979	0.435523	0.707690**	0.433042**
Value	0.222991	0.166425	0.740762**	0.167123*

*medium redundancy
** high relevance

In Table 7, besides the R^2 values, it is also possible to observe the redundancy of each of the latent endogenous variables. The redundancy of each latent endogenous variable links the predictive relevance of the measurement model with the structural model. It measures the percentage of variability in the indicators for the endogenous latent variable explained by its exogenous latent variables. The formula is given by the expression for the endogenous construct ξ_j:

$$Redundancy_j = Communality_j \times R^2\left(\xi_j, \xi_{q:\xi_q \to \xi_j}\right)$$

Being $R^2\left(\xi_j, \xi_{q:\xi_q \to \xi_j}\right)$ the coefficient of determination of the endogenous variable ξ_j. The obtained redundancy values do not significantly modify the evaluation made from the determination coefficients R^2.

The results of the cross-validation indices, especially the cv-redundancy, as this measure of Q^2 (as opposed to cv-communality) include the structural model in the forecast of the data, point in the same direction of R^2 and redundancy computed previously (Table 7). All values are above zero, providing support to the predictive relevance of the model for the six endogenous variables, with emphasis on satisfaction and complaint dimensions, where the values are large, followed by loyalty, value and empathy dimensions with medium values. The predictive relevance of the quality variable is the weakest, attested by the small values of R^2, redundancy and cv-redundancy (Table 7).

In order to globally evaluate the model, one resorted on a global fit measure proposed by Tenenhaus, Amato, & Vinzi (2004), called goodness of fit index, GoF (Duarte & Raposo, 2010). It represents the geometric mean of the weighted average communalities and the average of the determination coefficients R^2:

$$GoF = \sqrt{\frac{\sum_{q:n_q>1} n_q \times Comunalidade_q}{\sum_{q:n_q>1} n_q} \times \frac{\sum_{j=1}^{J_1} R^2\left(\xi_j, \xi_{q:\xi_q \to \xi_j}\right)}{J_1}}$$

This index, GoF, has a similar interpretation to that of the χ^2 test of the CB-SEM models, allowing evaluating the PLS-SEM model globally, taking into account the performance of the model in both its components, measurement and structural. Latent variables with a single indicator should not be used in this calculation, since communality is one (Tenenhaus *et al.*, 2005).

Its value oscillates between zero and one, and the better the adjustment the higher its value. This value is not directly calculated by SmartPLS software, so its calculation was done manually from the outputs provided. This index is considered large if greater than 0.36, medium if greater than 0.25 and small if greater than 0.1 (Wetzels, Odekerken-Schroder, & van-Oppen, 2009). The value obtained was $GOF = 0.459$, which means that the model has a large explanatory relevance.

5 RESULTS

The indices for the latent variables obtained by the proposed ISCFEE model were computed on a scale of 1 to 10, establishing, in terms of interpretation, the following subdivision: negative perception (indices below 4); neutral perception (indices between 4 and 6); positive perception (indices between 6 and 8); very positive perception (indices above 8).

The estimated complete model with the loadings of the measurement model, the impact coefficients and the indices of the structural model, are represented in Figure 6, values that allows one to identify the manifest variables on which to act in order to improve the customer satisfaction and loyalty.

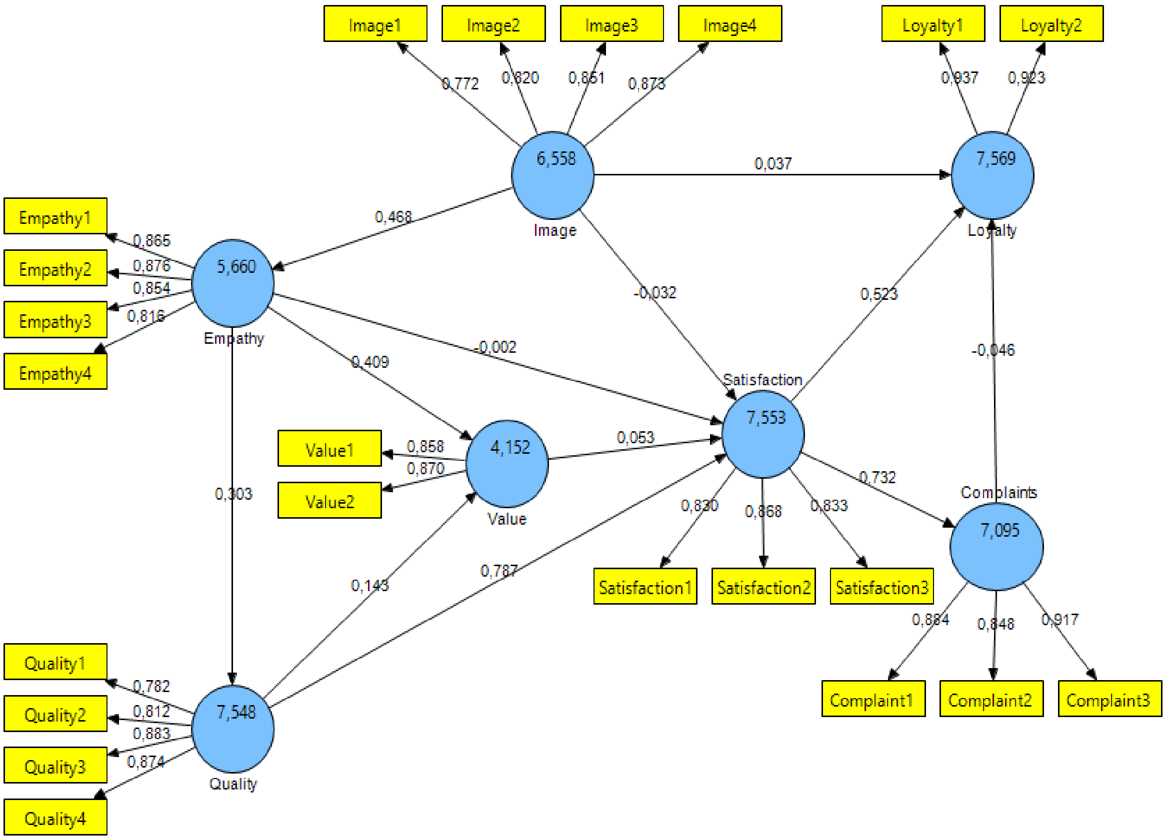

Figure 6 –ISCFEE Model
Source: Application of the PLS SEM *software* to the collected database.

The indices achieved for each variable, although not reaching the eight points to be considered of very positive perception, the quality of service, the satisfaction and the loyalty were very close. From positive perception, the complaints and the image and of neutral perception, the empathy and the value.

For comparative purposes with the ECSI Portugal 2012 model, the indices of the latter were rescaled to values from 1 to 10. The values of fundamental dimensions such as quality, loyalty, complaints and satisfaction, show an improvement, except for the image and the value which have worsened (Table 8).

Table 8 - Indices of the latent variables of the ISCFEE and ECSI Portugal models

	Proposed ISCFEE Model	ECSI Portugal 2012	ECSI Portugal 2012 (rescaled to values 1 to 10)
Empathy or Expectation	5.660 (Empathy)	7.06 (Expectation)	7.354 (Expectation)
Image	6.558	7.37	7.633
Loyalty	7.569	6.24	6.616
Quality	7.548	7.14	7.426
Complaint	7.095	6.64	6.976
Satisfaction	7.553	6.88	7.192
Value	4.152	5.23	5.707

Source: based on the output of the data analysis.

The comparison between the impact coefficients of the ISCFEE and ESCI Portugal 2012 models is found in Table 9, highlighting the impact of quality on satisfaction that almost doubled in the proposed model, which explains, in part, the increase in the perception of the central dimension of the model, the satisfaction.

Table 9 - Impact coefficients of the ISCFEE and ECSI Portugal models

	Proposed ISCFEE Model	ECSI Portugal 2012
Empathy (Expectation) -> Quality	0.303***	0.68
Empathy (Expectation) -> Satisfaction	-0.002	0.06
Empathy (Expectation) -> Value	0,409***	0.15
Image -> Empathy (Expectation)	0.468***	0.65
Image -> Loyalty	0.037	0.08
Image -> Satisfaction	-0.032	0.28
Quality -> Satisfaction	0.787***	0.40
Quality -> Value	0.143***	0.49
Complaint -> Loyalty	-0.046	0.13
Satisfaction -> Loyalty	0.523***	0.62
Satisfaction -> Complaint	0.732***	0.61
Value -> Satisfaction	0.053	0.19

6 CONCLUSIONS

A service should be started with the objective of offering quality to the customer and be completed by evaluating the perception the customer had about the service provided. Quality must be reflected in all the company's activities, not just in its services. The client is related to the entire structure of the company and tasks serve to support the provision of services, so quality must be present in all activities. Quality also requires total commitment from management and employees. Quality will only be achieved if all company employees and external service providers are trained, motivated and willing to collaborate on the best way to serve customers.

Quality requires highly competent partners. Any company that wants to provide quality services should select partners who also offer quality services, since the service provided can be modified in a positive or negative way by the partners' intervention. Quality can always be improved. The company should see continuous improvement in its activities through *Lean* or other continuous improvement tools for introduction and adjustment to activities across the enterprise. The use of benchmarking is also an example of how other organizations' best practices can be copied, refined and adapted to internal and external activities in order to broaden the quality standard offered to customers.

In this way, it is essential to develop adequate explanatory models of customer satisfaction, so that the company can better manage the service provided and increase customer satisfaction and loyalty.

In this study, a new structural model of customer satisfaction was developed and validated, the ISCFEE model, whose construction was based on the ECSI Portugal model, adapted to the energy distribution sector in Portugal. The model has as antecedent latent variables: image, empathy, perceived quality and value, with the central variable satisfaction and the consequent latent variables: complaint and loyalty.

The ISCFEE model was validated through the two submodels that make it up: the so-called measurement model and the structural model, which allows one to state that the model is adequate to measure service quality and customer satisfaction.

The model fulfilled the assumptions of establishing the impacts on measurable and latent variables and generating indices comparable to the ECSI Portugal model and it was verified that values of fundamental dimensions such as quality, loyalty, complaint and satisfaction exhibited indices higher than those obtained with ECSI Portugal. However, it was verified that there are three latent variables that need special attention by the the company, since two are in the neutral zone: value, empathy and also the image that, despite its perception being positive, its value substantially reduced compared to the ECSI Portugal model. It was found that quality of service has a significant impact on satisfaction and satisfaction has a significant impact on loyalty and complaint.

These results allow the company to take proper care to the indicators with below expected impact values and on which variables their attention should be prioritized.

7 LIMITATIONS

As the study was limited only to landline telephones of residential customers, in future research, it is suggested to also include customers with mobile phones, as currently many households do not have a landline.

In the future it would be interesting to analyze this type of model, not only assuming linear associations between latent variables, but also allowing non-linear associations between them. This can be done by relaxing the linearity assumptions of CB-SEM and PLS-SEM models.

It is also suggested the replication of this study with a broader sample in demographic terms, as well as a longitudinal study, with the goal of monitoring the indicators under study. Furthermore, the comparison with other competitors would allow EDP Distribution to adapt strategies and programs to increase the relative satisfaction of consumers.

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All the authors contributed to the accomplishment of this work.