

CUSTOMERS' SATISFACTION EVALUATION OF PORTUGUESE MOULD MAKERS BASED ON ECSI APPROACH

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Abstract

In recent years, the European Customer Satisfaction Index (ECSI) model has become a popular way of assessing customer satisfaction. Customer satisfaction and retention are considered as key issues for organizations in today's competitive market place, turning it into a vital concern to achieve customer loyalty. Therefore, it was necessary to develop one reliable and independent frame-of-reference of customer satisfaction, allowing the comparison between companies within the same sector and/or that operate in the same country, or at a macroeconomic level. The ECSI model is a framework, adapted from the Swedish Customer Satisfaction Barometer and American Customer Satisfaction Index, which aims to harmonize the Customer Satisfaction Indexes (CSI) in Europe. This paper describes one approach based on the ECSI model, developed to assess the satisfaction of Portuguese injection mould customers. Two main groups of customers were studied, the Portuguese and the American injection companies, where the data was collected by a self-respondent questionnaire sent by e-mail. The ECSI models were estimated according to two main techniques, the covariance-based or hard modelling methods (sometimes called LISREL) and the component-based techniques or soft modelling methods (e.g. Partial Least Squares). Therefore, it was possible to compare the satisfaction of the Portuguese and American customers, as well as comparing the performance of the two main techniques used to estimate the models.

Introduction

Customer Satisfaction (CS) and their retention are key issues for organizations in today's competitive market place, which makes its evaluation a main concern for companies and organizations in order to achieve higher levels of quality and customers' loyalty [1]. The European Customer Satisfaction Index (ECSI) model is a framework, adapted from the Swedish Customer Satisfaction Barometer and American Customer Satisfaction Index, which aims to harmonize the Customer Satisfaction Indexes (CSI) in Europe [2]. This model evaluated the CS as a latent construct because it assumed that CS is not directly

observed and can only be estimated through other indicators. In this sense, the basis for CS determination is the Structural Equation Modelling (SEM), which specified CS as sets of linear equations that model it as a function of its presumed cause-and-effect variables. These cause-effect relationships are then described by parameters that indicate the magnitude of the effect (direct or indirect) that independent variables (either observed or latent) have over dependent variables (either observed or latent). After that, the hypothesized relationships are translated into testable mathematical models, which must be tested against empirical data. The ECSI model adopted by Portugal is based on a structural model with seven latent variables, where each one is operationalised by multiple indicators, the measurement model. As a structural model, the CS is linked with four main drivers, namely, company image, customer expectations, perceived quality and perceived value, and with two main consequences namely, loyalty and complaints. Regarding CS antecedents, the ECSI model established Perceived Quality, which evaluates the recent consumption experiences concerning both quality of product and associated services, Perceived Value, which measures the "ratio" between the perceived quality of product and the price paid for it, Expectations, which includes the information that customers have acquired in the past regarding company' products and services, and Image, which embraces the global idea that customers have from the product and company. The consequences of CS considered in the ECSI model are Complaints and Loyalty. The variable Complaints evaluates the complaints frequency and the manner in which the company manages these complaints, and Loyalty measures customers' loyalty to the product or company. The way that each latent variable affect other variables included in the model are represented graphically by arrows (Figure 1). For example, Perceived Quality has been modelled to have a direct effect on CS, as well indirectly through Perceived Value. It is also expected that Perceived Quality is affected directly by Expectation, as well indirectly by Image. Technically, the previous model can be described through two sub-models, the structural model and the measurement model. The structural model includes the relations between latent variables that can be express according Eq. 1.

$$\eta = \beta\eta + \gamma\xi + v \quad \text{Eq. 1}$$

Where η is the vector of endogenous latent variables (which consists of six latent variables, such as Expectations, Perceived Quality, Perceived Value, Customer Satisfaction, Loyalty and Complaints), and ξ is a vector of an exogenous latent variable (Image). The coefficients of the structural model, β and γ , give the direct impact on a latent variable when there is a unit change in an antecedent latent variable. If the antecedent variable is an exogenous variable, the direct impact is represented by γ , while β represents the direct impact over endogenous variables derived by a unit variation of another endogenous variable. The vector of specification residuals for the endogenous latent variables η is represent by v . Regarding the measurement model, which establishes the relations between the latent variables and the observed indicators, there are three possible types of measurement models, reflective models (or outwards directed models), formative models, and mixed models. A reflective model exists when the observed variables are assumed to be the reflex of the latent variables, which is typical for endogenous variables where the manifests are reflections of the underlying latent variables. Therefore, the reflective models can be technically described as Eq.2 and Eq.3.

$$x = \Lambda_x \xi + \delta \quad \text{Eq. 2}$$

$$y = \Lambda_y \eta + \varepsilon \quad \text{Eq. 3}$$

Where x and y are manifest vectors, respectively the exogenous and the endogenous ones. Λ_x and Λ_y are the correspondent weight matrices (loadings) and, finally, δ and ε are measurement error vectors. In opposition, the formative model assumed that the observed variables are supposed to cause or form the latent variables. Therefore, if the latent variable is formed by the manifest variables, one can express the exogenous variable ξ according Eq.4.

$$\xi = \sum_{l=1}^G \lambda_{\xi_l} x_l + \delta_{\xi} \quad \text{Eq. 4}$$

Where λ_{ξ_l} are coefficients of the formative model and δ_{ξ} are specification errors. Finally, the mixed model adopts both models, where generally the formative is used for the exogenous latent variables, and the reflective model is employed for the other latent variables. The ECSI model adopted by Portugal is based on a mixed model, where Image is measured by indicators which are their cause (formative), and all the other variables are established as a reflex of its indicators. Afterwards, it is necessary to define which indicators are adequate to measure each latent variable in order to enclose properly the specific characteristics of product or service whose intend to be evaluated. After the indicators are determined, one standardized measurement

instruments (or questionnaire) must be developed. The scale used in these instruments is normally chosen to create enough variation in the data, in order to support a statistical analysis, and where equidistance has shown some advantages [3]. In this sense, the majority of national indexes within ECSI are based on a 10-point scale (1 - completely disagree and 10 - completely agree), where the customer satisfaction index and all other latent variables are transferred to an index ordinary scale of 0 to 100, where 100 denotes the highest possible value.

European Customer Satisfaction model (ECSI) specific for injection moulds sector

In order to build the measurement model in an accurate way of assessing the particularities of injection mould makers sector, we carried out firstly one qualitative phase that aimed to identify the concepts to measure and to elicit a comprehensive set of questions that are potentially relevant in measuring these concepts. Therefore, at this first stage an illustrative sample of customers of national mould makers where inquired through a semi-structure interview. The interview includes three main groups of questions. The first one aims to identify the customers' requirements regarding product quality, while the second part intends to perceive the customer needs and expectations regarding the services provided. The last part of the interview means to know customer perspectives for the future as a way to evaluate their real satisfaction and loyalty levels. The information gathered from the interviews, which was complement and structured by the KJ method, allowed to identify the factors (drivers) that might contribute, towards perceived quality of product and service, to customer satisfaction. These factors are Quality of mould's design, Quality of the moulds' construction, Cooperation, Resources, Response Capacity and Contracts (Figure 2). Afterwards, generic questions as multiple indicators (at least two) were developed for each one of the latent variables in order to construct the standardised questionnaire (see Table 1). Data collection was performed by sending a self-respondent questionnaire directly to Portuguese and American injection companies (who are/or were mould makers' customers). Regarding the Portuguese injection companies, the data was gathered during spring and summer of 2007 by asking all Portuguese companies with CAE equal to 25240. Similarly, the American injection companies were inquired during the spring of 2008, where the survey was sent by email to all the injection companies register with Standard Industrial Classification (SIC) equal to 308901.

Portuguese versus American injection costumers

Based on the data gathered, and regarding the values obtained for each latent variable, it is possible to compare graphically the answers of Portuguese and American companies, customers of national mould makers (Figure 3). Therefore, it is possible to observe that, in average, the American companies customers of Portuguese mould makers are must more satisfied (for all the items). One possible justification for this evidence can be related with the company's size, since in average Portuguese customers order 15 moulds per year while American order 100 moulds per year, which means that the American companies are bigger and it is most likely that the importance of these companies for the national mould makers is proportional to their size (and consequently volume of orders). Even though the higher values obtained for American's companies, it is interesting to note that the distinction between the different latent variables is similar for the two groups of costumers (with only two exceptions, Image and Complaints). For instance, both companies qualified Value as the weakest point of Portuguese mould's makers.

Model estimation

In order to determine the parameters of the model, there are two main types of techniques that can be used, namely the covariance-based or hard modelling methods and component-based techniques or soft modelling methods (e.g. Partial Least Squares (PLS)). The covariance-based techniques estimate path coefficients and loadings by minimizing the difference between the observed (obtained by the data gathered) and the predicted variance-covariance (defined by the hypothesized model) matrices. The estimation can be undertaken by some different estimation procedures, although the most widely used is the Maximum Likelihood (ML). The component based approach, i.e. PLS technique, estimates parameters, similarly to the principal component technique, through a multiple regression basis. Therefore, the PLS algorithm generates iteratively the estimates of latent scores based on inner (relations between the latent variables) and outer relations (relations between a latent variable and its associated indicators), until the two relations converge. PLS is called Partial Least Squares because it studies a system of linear relationships between latent variables by solving blocks (combinations of theoretical constructs and measurements) one at a time (partial) by use of interdependent Ordinary Least Squares (OLS) regressions. Based on all of this, the main question is leaving one to sort out which technique to use. Since the instigation of the national CSI,

PLS has been used to estimate the CSI models, in preference to the Covariance based methods, mainly because PLS doesn't rely on strict assumptions about the data (specifically about the normality assumption) [4]. In this sense, the covariance based approach is not recommend, since the probability density function of the measured variables is not generally symmetrical, even if one adopts a scale of 1 to 10, and the values of the measured variables are likely to be highly collinear. Additionally, the inexistence of assumptions about indicators' statistical distribution, the no need for independent observations and the possibility of use formative or/and a reflective model, reinforced the option for PLS methods. The preferences for PLS approach have being suggested by Vilares et al. (2005) [2] and Cassel et al. (2000) [5]. By the contrary, some authors believed that the PLS option was based upon some misconceptions about the use of Covariance based methods, and don't take into consideration the recent advances in this area, in particular, the estimation methods that are robust to non-normality and missing data. For instance, O'Loughlin et al. (2002) [6] compared six different approaches, five based on covariance-based with ML estimation and one based on PLS, and found that the new robust ML procedure was more advantageous than PLS method. One brief comparison of these two techniques is illustrated in Table 2 [7]. In this context, it should be interesting to estimate ECSI model parameters, previously defined, by carrying out both approaches. Although, since the data gathered in this study does not follow a multivariate normal distribution and the sample is smaller when compared with the typical ECSI studies, the basic assumptions for covariance based approach estimation are not accomplished. Therefore, following the alternative approach suggested by Fornel et al. (1992) [8], the reduced ECSI model will be used instead. The ECSI reduced model specific for mould's makers, which can be observed in Figure 4, was obtained by Image and Complaints removable.

Covariance based estimation

Due to the non-normality of the data gathered, one alternative method must be undertaken in order to overcome this limitation. One of these methods is the Robust Maximum Likelihood (RML) method, which was considered robust to the non-normality of data and adequate for small sample sizes [6]. The basis for this method is the Asymptotic Covariance Matrix (ACM) which adjusts the normal theory weight matrix in order to get less biased chi-squared statistics and standard errors. Therefore, the RML estimation was carried out by LISREL 8.8, on the complete data set obtained by mean substitution. Additionally, we imposed that the Variance of Expectations

(exogenous variable for the reduced model) must be equal to 1.00 and the Error Variance of Value must be equal to 0.005 (in order to correct the improper solutions, such as the negative variance for error). The ACM was computed by PRELIS 2.8. Following Hulland (1999) [9] recommendations, Loyalty_2 was dropped out because its estimated loading was lower than 0.5, which means that there is fewer shared variance between the construct and its measure than error variance, and the model fitting was assessed, i. e. determining how reasonably the model represents the observed data. The overall model fit was assessed statistically by the χ^2 test, and heuristically by using the adequate fit indexes proposed by Hue and Bentler (1990) [10]. Regarding some additional issues, like the smaller sample size [11], the non-normality of data [12-13], and the existence of Missing Data (MD) [14], the more appropriate indexes and respective cut-off values are described in Table 3, which indicates that the tested model must be accepted. After that, the analysis was proceeded with the evaluation and interpretation of the estimated model parameters. This task was undertaken through the t-ratio, which assesses the significance of individual parameters where values lower than 2 are considered non-significant and can be removed from the model without causing a significant decrease in fit (red highlighted). The final model parameters estimated through covariance based approach can be observed in the Figure 5.

Component based approach

In order to carry out the component based approach, the missing data are replaced by the mean of respective variable on the available data. The need for manifest variables standardization was introduced by Lohmöller who established a standardization parameter called METRIC. Since, in the ECSI model the variables scales are equal, the means are interpretable and the variance is related to variance importance, we adopted the METRIC 4, which means that the PLS algorithm must be applied to the raw manifest variables (e.g. manifest variables are not centred neither standardized). Regarding the latent variables, they must be standardized through Internal and External estimation. About Internal estimation, there are three schemes that can be followed, but according to Esposito et al. (2002) [15] the different weighting schemes do not show significant differences, so we opted by the Centroid Scheme. Regarding the External estimation, the Mode A was selected for all latent variables, where the starting vector of weights assumed all values equal to 1. This option follows Esposito et al. (2002) recommendations, where they pointed this option as the most adequate

when all weights are positive. In case of negative signs encountered, they recommended that the related manifest variables must be removed from the model. The software used to undertake the PLS estimation was the SmartPLS Beta version 2.0 (<http://www.smartpls.de>).

Since, contrarily to the covariance-based approach, the component-based approach haven't proper overall goodness-of-fit measures and because doesn't exist any kind of assumption regarding indicators and standard error distribution, there are two main groups of techniques that are usually used in PLS approach to validate the model (both no parametric). The first one, which aims to determine the quality of adjust and to predict the explaining capacity of the model, includes the computation of determination coefficients R^2 and the Average Variance Extracted (AVE). The second group intends to test the parameters estimates and can be determined by Jackknife or Bootstrap techniques [16]. In this sense, and according Tenenhaus et al. (2002) [17] recommendations, the resampling procedure used to validate the model was Bootstrap with Individual Change, which pointed out that Expectations-ECSI and Value-ECSI are non significant paths (Figure 6).

Comparison between the two approaches

Theoretically, the main differences between PLS and covariance methods estimations come from the order in which model parameters and latent variables are calculated, and from the constraints on these ones. With PLS, latent variable estimates are first computed subject to the constraint that they must belong to their manifest variable space. Model parameters are then computed using OLS multiple regression. With covariance-based methods, model parameters are computed by ML (or GLS), and few constraints are imposed on the latent variables. Therefore, the latent variables estimation does not play any role in the model estimation. Based on this, it may be expected that the structural equations are more significant with covariance-based methods than with PLS (the coefficient of determination are larger) and the correlations between the manifest variables and their latent variables are stronger with PLS [17].

Regarding the results obtained for our ECSI reduced model, and comparing the quality of estimated parameters (measured by coefficients of determination) and model loadings for measurement indicators, it is possible to verify that the differences between the two approaches results are: covariance-based methods increases the coefficients of determination (R^2) for the structural model (Figure 7) and PLS increases the loadings for the measurement model (Figure 8).

This occurs because, as it was already mentioned, PLS procedure estimates the latent variable as a linear combination of its manifest variables, so the measurement model is favoured, and in covariance-based methods because each latent variable is estimated by regression of the "theoretical" latent variable on the whole set of own manifest variables, the structural model is favoured. Nevertheless, it is possible to conclude that both methods give identical estimates, where it's possible to verify that the minimum R^2 for CS is 0.78 (PLS approach) which is very much satisfactory, even considering the complexity of the model. Regarding the factors that might contribute toward CS, since we used the reduced ECSI model which establish only Expectations and Value as CS antecedents, and considering that these paths are non significant, it was no possible to identify at this stage which factors explain the high value obtained for ECSI.

Conclusions

This paper describes one approach, based on the ECSI model, which aims to assess the satisfaction of Portuguese injection mould customers in a reliable and independent frame-of-reference. This framework allowed the comparison between two main groups of customers, the Portuguese and the American injection companies. The comparison between the two groups pointed out that the American companies are more satisfied with the Portuguese mould makers than the national companies. This evidence can be explain by the difference of company's size that belong to at each group, where it is possible to verify that the number of moulds ordered per year is almost 7 times superior for the American customers.

Regarding the estimation of the proposed ECSI model, and since the data gathered by the self-responder questionnaire sent by e-mail encompassed a small sample size characterized by non normal distribution, it was not possible to carry it out it through the covariance-based methods (due to its restrictive assumptions about the data). Therefore, in order to compare the performance of the two main techniques used to estimate the models, namely covariance and component based methods, we used one reduced ECSI model obtained by Image and Complaints removal. The covariance based method was undertaken by LISREL 8.8/Prelis2.8 through RML as the estimation method, where the missing data was substituted by each variable means. Regarding the component-based approach, it was carried out by SmartPLS Beta version 2.0 with missing data substituted by the Means. Comparing the models estimated by the two approaches, it is possible to verify that the covariance approach

gives better results for the structural model (showed by the higher values of R^2), essentially because its presumption of space-free, while PLS gives better results for the outer model (illustrated by the correlations between the manifest variables and their latent variables), since each latent variable is constrained to be in its own manifest variable space. Anyway, it is also possible to conclude that both methods give identical estimates, where the minimum R^2 for CS is 0.78 (PLS approach) which is a very satisfactory value.

Keywords

ECSI, Customer satisfaction, Structural Equation Model, Covariance based and PLS.

Bibliography

- [1] Ferreira, I., J. S. Cabral, et al. (2007). A new conceptual framework based on the ECSI model to support Axiomatic Design. Virtual and Rapid Manufacturing. P. J. B. e. al, Taylor&Francis.
- [2] Vilares, M. J., M. H. Almeida, et al. (2005). Comparison of likelihood and PLS Estimators for Structural Equation Modeling. A simulation with Customer Satisfaction Data. 4th International Symposium on PLS and related methods, Barcelona.
- [3] Coelho, P. S. and S. P. Esteves (2007). "The number of categories for a scale." International Journal of market research.
- [4] Ball, D., M. Vilares, et al. (2003). A new explanation for customer loyalty: an application with the ECSI model. PLS'03 "Focus on customer" - PLS and related methods, Lisbon, Decisia
- [5] Cassel, C., P. Hackl, et al. (2000). "On measurement of intangible assets: a study of robustness of Partial Least Squares." Total Quality Management 11(7): 897-908.
- [6] O'Loughlin, C. and G. Coenders (2004). "Estimation of the European Customer Satisfaction Index: Maximum Likelihood versus Partial Least Squares. Application to postal services." Total Quality Management 15(9-10): 1231-1255.
- [7] Hsu, S.-H., W.-H. Chen, et al. (2006). "Robustness Testing of PLS, LISREL, EQS and ANN-based SEM for measuring customer satisfaction." Total Quality Management 17(3): 355-371.
- [8] Fornell, C. (1992). "A National Customer Satisfaction Barometer: The Swedish Experience." Journal of Marketing 56 6-21.
- [9] Hulland, J. (1999). "Use of Partial Least Squares (PLS) in strategic management research: a review of four studies." Strategic Management Journal 20: 195-204.
- [10] Hu, L.-t. and P. Bentler (1999). "Cutoff Criteria for Fit indexes in Covariance Structure Analysis: Conventional criteria versus new alternatives." Structural Equation Modeling 6(1): 1-55.
- [11] Gerbing, D. W. and J. C. Anderson (1992). "Monte Carlo Evaluations of Goodness of Fit Indices for Structural Equation Models." Sociological Methods & Research 21(2): 132-160.
- [12] Curran, P. J., S. G. West, et al. (1996). "The Robustness of Test Statistics to Normormality and

Specification Error in Confirmatory Factor Analysis." Psychological Methods 1(1): 16-29.

[13] Lei, M. and R. G. Lomax (2005). "The effect of varying Degrees of Nonnormality in Structural Equation Modeling." Structural Equation Modeling 12(1): 1-27.

[14] Davey, A., J. Savla, et al. (2005). "Issues in Evaluating Model Fit with Missing data." Structural Equation Modeling 12(4): 578-597.

[15] Esposito, V., C. Lauro, et al. (2002). Methodological Specifications. E. Consortium.

[16] Chatelin, Y., V. Vinzi, et al. (2002). State-of-art on PLS Path Modeling through the available software, ESIS.

[17] Tenenhaus, M. (2003). Comparison between PLS and LISREL approaches for structural equation modeling: application to the measure of Customer Satisfaction. PLS'03 "Focus on customer" - PLS and related methods, Lisbon, Decisia

Illustrations

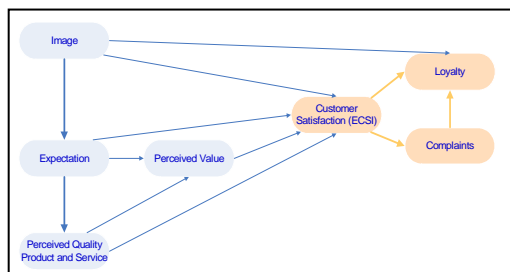


Fig. 1. The ECSI Model adopted by Portugal

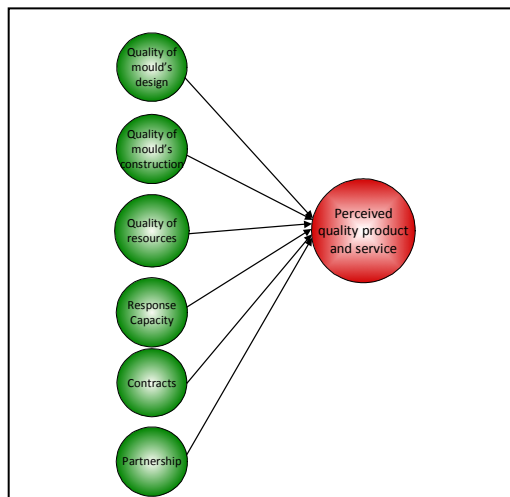


Fig. 2. The main factors which contribute towards Perceived Quality

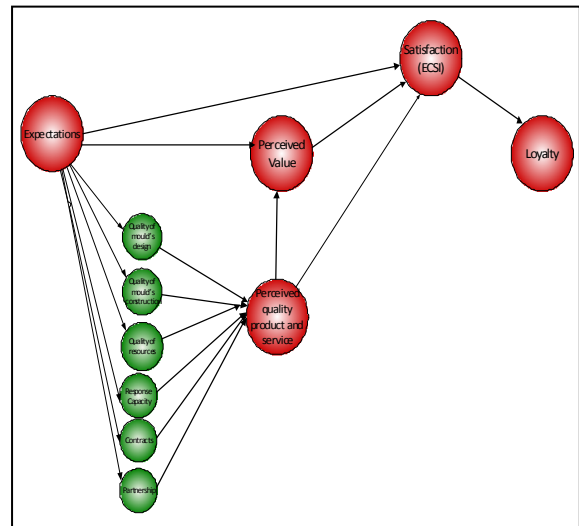


Fig. 3. The reduced ECSI model specific for mould's makers sector

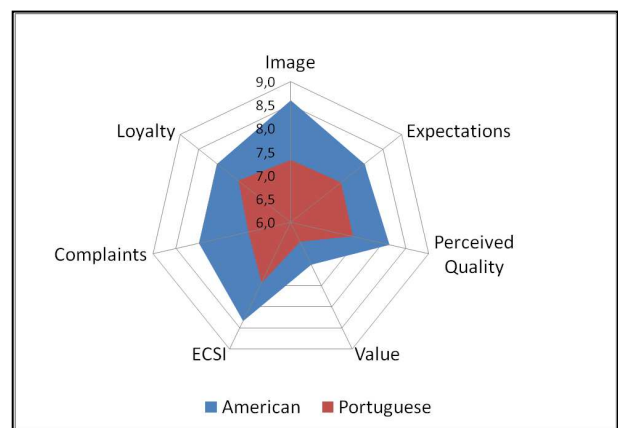


Fig. 4. Comparison between American and Portuguese costumers

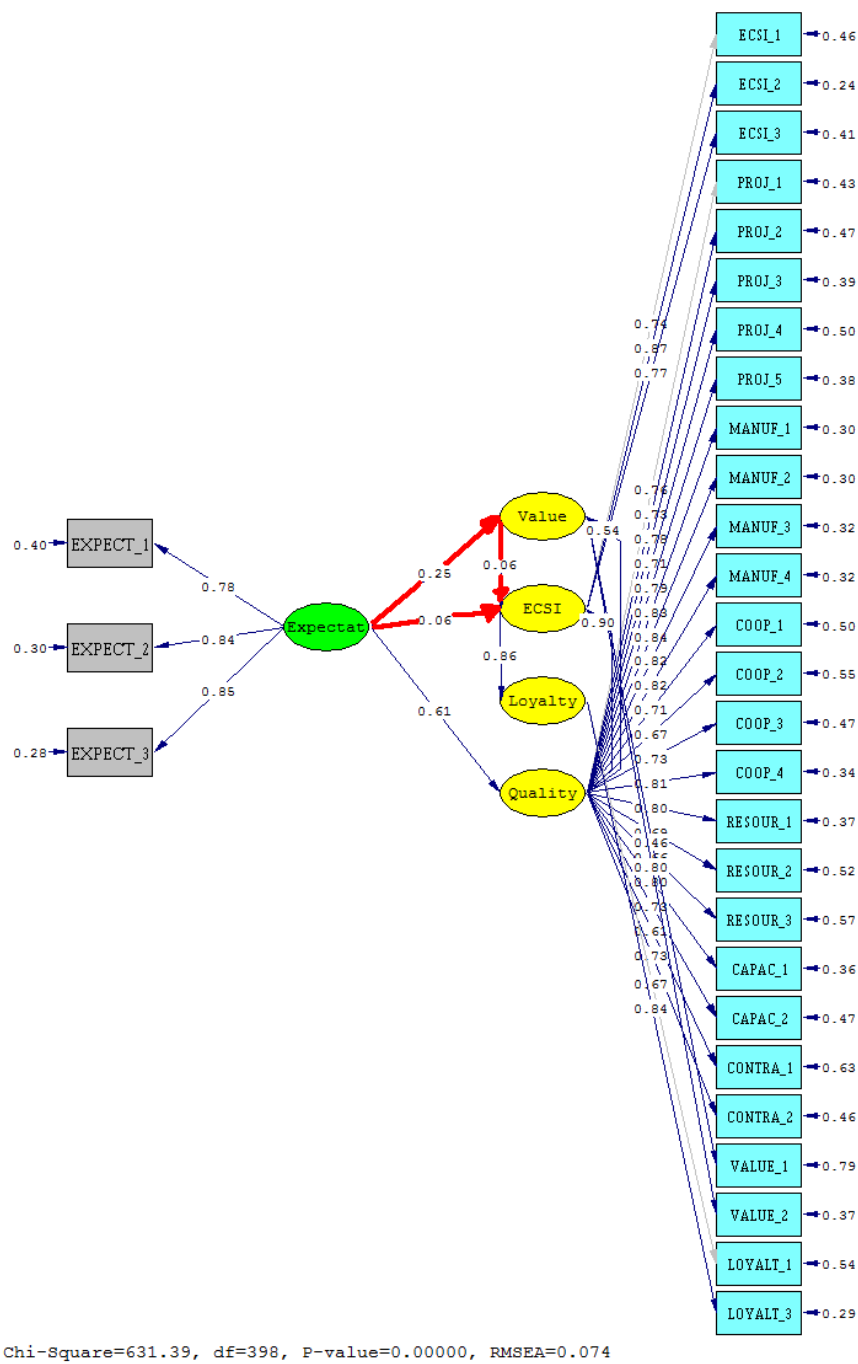


Fig. 5. The reduced ECSI model specific for mould's makers sector: standardized estimates (red highlighted non significant paths)

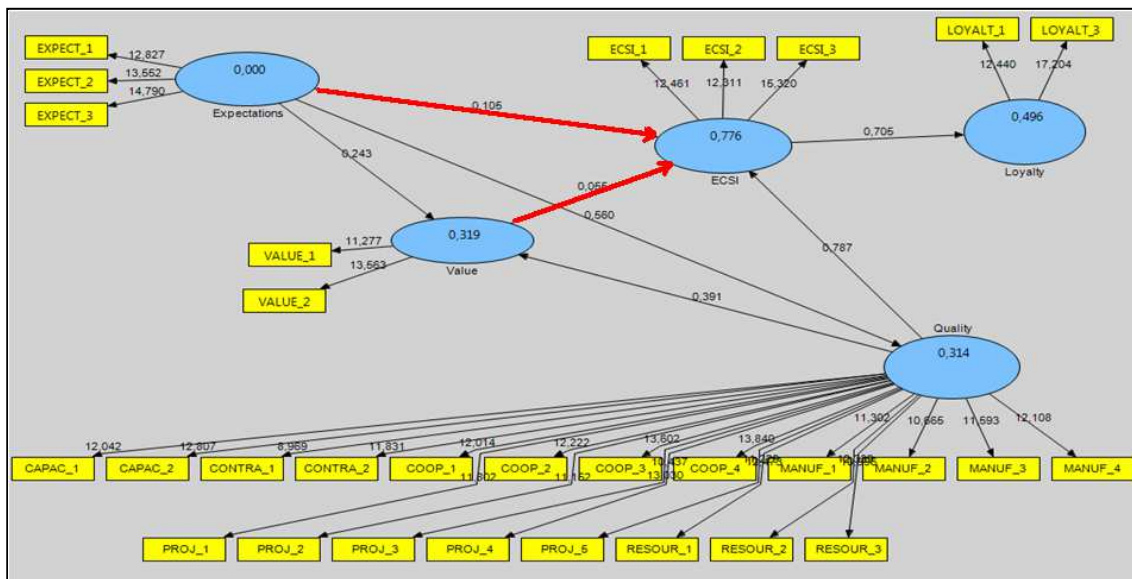


Fig. 6. The final model parameters estimated by PLS (red highlighted non significant paths)

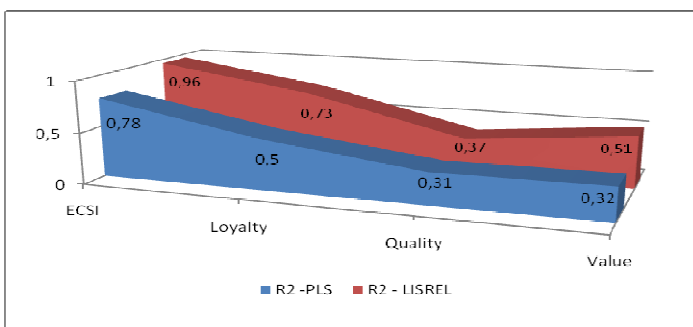


Fig. 7. Quality of estimated model measured by R^2

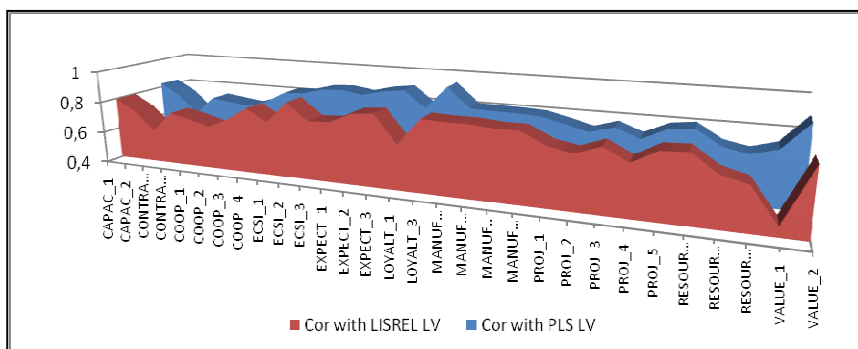


Fig. 8. Measurement model loadings

Table 1. The questions used as indicators per each latent variable

Latent variables	Observed variables
Image	This mould maker is a reliable and trustworthy company This company is innovative and always looks ahead This company is a customer-oriented company This company has lots of experience in moulds production This company is stable and well established
Expectations	Overall quality of this company Company's capacity in offering moulds that answer to customer needs Moulds makers' reliability and provided service

Quality of the mould's design	The capacity of the mould's design meeting customer's product requirements The mould's design capacity according to the customer's specific injection process Adequacy of constructive solutions The company's accessibility in discussing the mould's design The overall quality of the mould's design
Quality of the moulds' construction	Quality of the structural elements Reliability of the adopted constructive solutions The adequacy of manufacturing processes (type, parameters and tools) to customer requirements The overall quality of the mould's construction
Cooperation	The company's accessibility in sharing responsibilities for the part's quality The following up of the mould performance during its life cycle Company's pro-activity in collaborating in solving problems during the mould's life cycle Capacity for integrating complementary services
Resources	The technical staff's know-how Level of its high-tech equipment Quality of the installations
Response capacity	Response capacity to the customer's requirements Capacity in answering quickly to the customer's needs and problems
Contracts	The company's flexibility The fulfilment of the conditions previously agreed
Perceived value	Quality of product/service given the price paid Prices of product/service given the mould's quality
Customer Satisfaction	Overall satisfaction with the company's products and service Considering customer expectations, to what extent have the company fulfilled them How close is the company to customer ideal provider
Complaints	How many times have things gone wrong Identify who have complained How well was the last complaint handled
Loyalty	How likely will you order from this company a new mould Recommend this company to others Sensibility to price changes

Table 2. Comparisons of covariance-based and component-based SEM technique [7]

Feature	Covariance-based approach	Component-based
Distributional assumptions	Multivariate normal distribution	None
Purpose	Theory oriented	Prediction oriented
Parameter estimates	Consistent	Consistency at large
Hypothesis testing	Available	Inference requires Jackknife or bootstrapping
Sample requirement	Large	Small
Parameter identification problems	Not convergence or improper solutions	Few
Latent variables scores	Factor indeterminacy	Explicitly estimated
Reflective and formative relations	Only reflective relations	Both

Table 3. The Goodness-of-Fit values obtained by covariance-based approach

Index	Cut-off criteria	Model
SB χ^2	-	631,39
df	-	398
RMSEA	≤ 0.08	0,074
TLI or NNFI	> 0.95	0,98
CFI	> 0.95	0,98
SRMR	≤ 0.08	0,057