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AN APPLICATION OF THE STRUCTURAL EQUATION MODELS TO CUSTOMER SATISFACTION AND LOYALTY ASSESSMENT

Riccardo Di Nisio*, Tonio Di Battista
Department of Quantitative Methods and Economic Theory
University of G.d'Annunzio, Chieti-Pescara, Italy

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***Abstract**: Customer satisfaction is a key issue for the organizations in the today's competitive market. As such, much research and a lot of revenues have been invested in developing accurate ways of assessing consumer satisfaction at macro (national) or micro (organizational) level, facilitating comparisons of the performances between industries.*
To this purpose since 1994 different national customer satisfaction indexes (CSI) have been proposed. American Customer Satisfaction Index (ACSI) and European Customer Satisfaction Index (ECSI) are the two most popular indexes. Their implementations are usually developed at the macro level, and suitable applications at micro level have not yet been proposed. This absence is the main cause of a large proliferation of different models that, in many cases, do not make possible the comparison of CSI within and between industries.
To enhance the comparison properties of this index an adaptation of ACSI and ECSI models to a specific economic sector is proposed. Furthermore, according to [18], *the antecedent "expectation", not significant at the micro economic level* [13], *was removed and two new antecedents, "belief" and "leadership" were introduced.*
The goodness of the estimated model was confirmed by an application to a network of 250 firms operating in the building retailers.
The PLS (Partial Least Squares) approach has been proposed for the estimation phase. Data were collected during the summer of 2009 by means of a 15 items questionnaire given to 250 managers.

***Keywords**: Customer satisfaction, structural equation model, ACSI, latent variables, partial least squares.*

*Corresponding Author. Email: dinisio@unich.it

1. Introduction

Customer satisfaction has become a vital concern for companies and organizations in their efforts to improve product and service quality, and maintain customer loyalty within a highly competitive market. In the last decade, a number of national indicators reflecting consumer satisfaction across a wide range of organizations have been developed (e.g., [1], [7], [10] and [18]). At the national level, the customer satisfaction index (CSI) is a nationwide gauge of how adequately companies, and industries in general satisfy their customers. In addition, CSI's can be used at company level, facilitating comparison of companies within an industry. These indicators complement the traditional measures of economic performance (e.g., return on investment, profit and market share) providing useful diagnostics about organizations, and their customers evaluations of the quality of products and services.

2. Factors within the ECSI/ACSI Model

The basic structure of the CSI model has been developed over a number of years and is based upon well-established theories and approaches to consumer behaviour, customer satisfaction and product and service quality (see [7] and [10]). The structure of the CSI is continually undergoing review and subject to modifications. Although the core of the model is in most respects standard, there are some differences between the SCSB (Swedish), the ACSI (American), the ECSI (European), the NCSB (Norwegian) and other indices. For example, the image factor is not included in the ACSI model although plans are underway to include this factor into this model, [13].

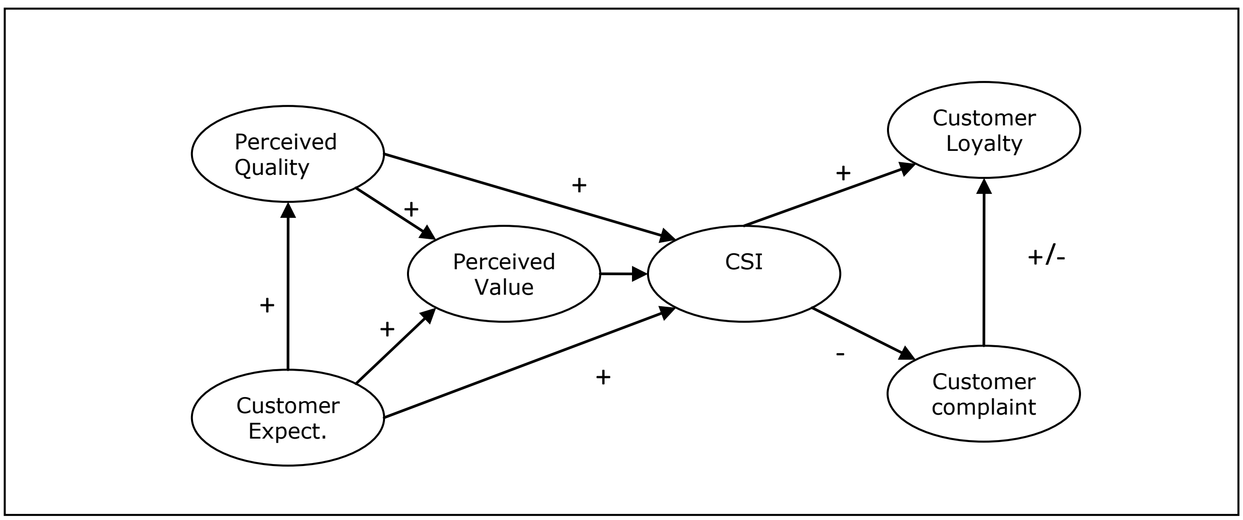

Figure. 1 The ACSI model

In order to evaluate the CSI, the ACSI model (Fig. 1) considers a proper set of latent factors, each of them is linked to multiple indicators. Customer satisfaction (CSI) can be defined as an overall post-purchase evaluation of a product performance or of a service utilization [7].

2.1 Antecedents of customer satisfaction in ACSI model

In the ACSI model the antecedents variables are:

Perceived Quality: it may be defined as the average between two general types of perceptions: product quality (hardware) and service quality (software/humanware) [10]. Perceived product quality comes from the evaluation of recent consumption experience of products. Perceived service quality is the evaluation of recent consumption experience of associated services like customer service, conditions of product display, range of services and products. This distinction between service quality and product quality is a standard feature of the ECSI model [6].

In [16] the importance of delineating these two aspects of perceived quality in a post office context is showed. Both types of quality are expected to have a direct and positive effect on the overall customer satisfaction.

Perceived Value: the literature in this area has recognised that customer satisfaction is dependent on value [12]. Value is the perceived level of product quality relative to the price paid or the "value for money" aspect of the customer experience. Value is defined as the ratio of perceived quality relative to price (Anderson *et al*., 1994) [1].. Value is expected to have a direct impact on satisfaction, [1] and [7].

Customer Expectations: refer to the level of quality that customers expect to receive and are the result of prior consumption experience with products or services. In [13] it was noted that the effect of expectations is not significant in a number of industry sectors. Similarly, in [18] it is showed that customer expectations of products and services in Denmark have a negligible impact on consumer satisfaction. Thus, the expectations construct was not included in this paper. Instead of customer expectation we introduce the "belief" as the reliable of the firm perceived through Internet.

2.2 Consequences of consumer satisfaction

Customer Complaints: refers to the intensity of complaints and the manner in which the company manages these complaints. It is expected that an increase in customer satisfaction should decrease the incidence of complaints, [10].

Customer Loyalty*:* Customer loyalty is the ultimate dependent variable in the model and is seen to be a proxy measure for profitability, [19]. Increasing customer loyalty secures future revenues and minimises the possibility of defection if quality decreases. In addition, word-of-mouth from satisfied loyal customers embellishes the firm's overall reputation and reduces the cost of attracting new customers, [2]. Loyalty is measured by repurchase intention, price tolerance and intention to recommend products or services to others. It is expected that better image and higher customer satisfaction should increase customer loyalty. In addition it is expected that there is a reciprocal relationship between complaints and loyalty. When the relationship between customer complaints and customer loyalty is positive it implies that the firm is successful in turning customers who complain into loyal customers. Conversely, it is expected that when the relationship is negative the firm has not handled complaints adequately.

3. The proposed model

Starting from the ACSI and ECSI models we proposed to remove the "Customer Expectation" and to introduce the following two new variables: "belief" and "leadership". The first one is finalized to point out the internet role in the customer satisfaction. The second one is finalized to detect the role of the management of a firm. The new scheme is shown in Fig. 2. The observed variables connected to each latent variable are listed into the following Table 1.

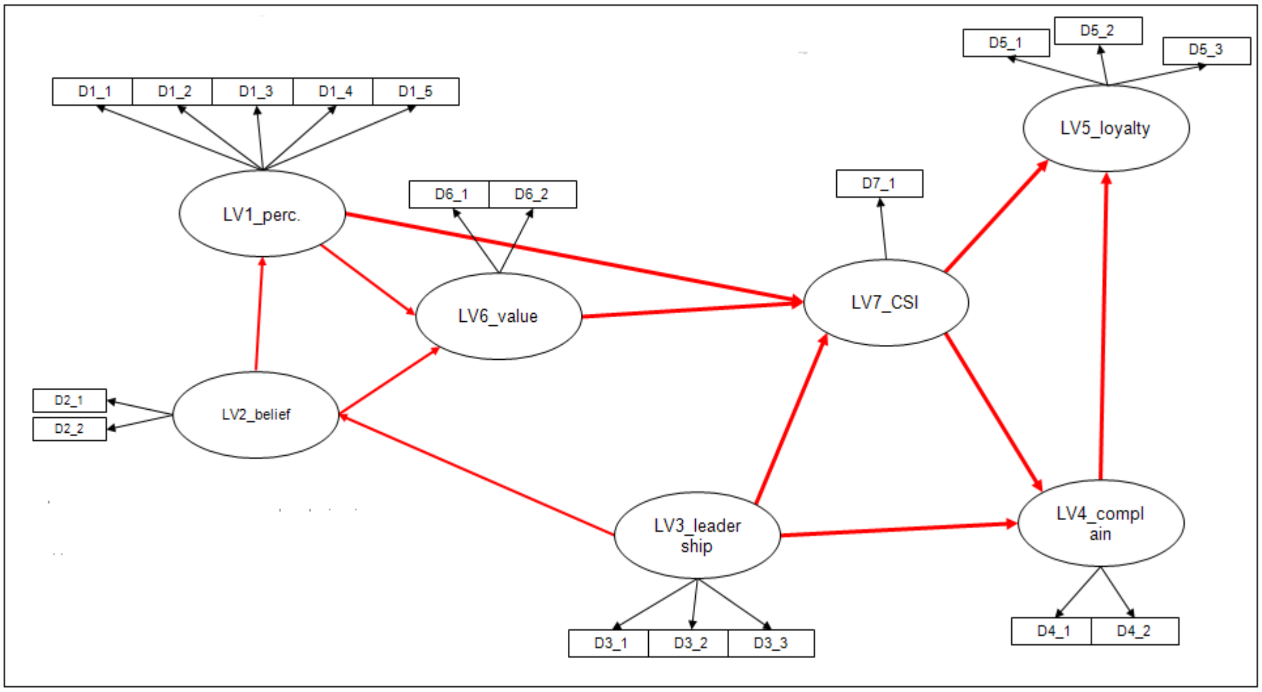

Figure 2. The model proposed for the Customer Satisfaction index

Table 1. Latent variables and manifest variables used in the model

LATENT VARIABLES	MANIFEST VARIABLES	CODE
Perceived Quality	Expectations about the overall quality when you become client	D1_1
	Expectations about the ability of the service to meet the needs	D1_2
	Possibility that the services prove unsatisfactory	D1_3
	Expectations about the timing	D1_4
	Expectations about the reliability of services	D1_5
Belief	Confidence about the information found through Internet	D2_1
	Confidence in the image of the group	D2_2
Value	Value for money	D6_1
	Supplies Reliability	D6_2
Leadership	Managerial ability	D3_1
	Listening skills	D3_2
	Problem solving	D3_3
CSI	Overall Satisfaction	D7
Loyalty	Re-purchase willing of the products / services	D5_1
	Positive word of mouth	D5_2
	Purchasing from competing suppliers	D5_3
Complaints	Number of complaints	D4_1
	Negative word of mouth	D4_2

In order to estimate the model, the Partial Least Squares algorithm, PLS, has been suggested, [22] and [7]. This approach was grounded on the argument that the other procedures, used to estimate these models (covariance structure analysis models, also called LISREL, from the name of the first commercial software that became available, developed by Jöreskog, [14] (see [4] or [3] as introductory works), make more strict assumptions on the model structure and on the data, mainly regarding identifiability and normality.
The PLS (Partial Least Squares) approach to Structural Equation Models, also known as PLS Path Modeling (PLS-PM) has been proposed as an alternative estimation procedure to the LISREL-type approach to Structural Equation Models. In Wold's [22] seminal paper, the principal component analysis approach was extended to situations with more blocks of variables. The first presentation of the PLS Path Modelling is given in [23], and the algorithm is described in [24] and [25]. An extensive review on PLS approach to Structural Equation Models is given in [5] and [21].
As all the component-based estimation techniques, PLS Path Modelling is an estimation method based on components. It is an iterative algorithm that separately estimates the unknown values of the latent variables and then, in a second step, estimates their regression or structural coefficients. Differently from LISREL-type estimation techniques, PLS Path Modelling aims at explaining at best the residual variance of the latent variables and, potentially, also of the manifest variables in any regression run in the model, [8]. That is why PLS Path Modelling is considered an explorative approach instead of a confirmative one: it does not aim at mainly reproducing the sample covariance matrix.
PLS Path Modelling aims at estimating the relationships among Q blocks of observed variables, which are expression of Q unobservable constructs. Specifically, PLS-PM estimates through a system of interdependent equations based on simple and multiple regressions, the network of relations among the manifest variables and their own latent variables, and among the latent variables inside the model.
Formally, let us assume P variables X_1, X_2, …, X_P observed on N units. The observations x_{npq} ($n=1,...,N$; $p=1,\dots,P$; $q=1,\dots,Q$) are called manifest variables and assumed to be centred. Unless explicitly stated, they are also assumed to be standardized. Hence the data are collected in several blocks and may be represented in the following matricial form:

$$\mathbf{X} = \left[\mathbf{X}_1, \dots, \mathbf{X}_q, \dots, \mathbf{X}_Q\right] \tag{1}$$

where $\mathbf{X}_q$ is the generic q-th block. Each block of variables is considered to constitute the observable expression of a latent variable ξ_q ($q=1,\dots,Q$) with zero mean and unit variance.
Let the structural equation model among the endogenous $\boldsymbol{\xi}^{(j)}$ and exogenous $\boldsymbol{\xi}^{(M)}$ latent variables vectors be defined as:

$$\boldsymbol{\xi}^{(j)} = \mathbf{B}^{(j)}\,\boldsymbol{\xi}^{(j)} + \mathbf{B}^{(M)}\,\boldsymbol{\xi}^{(M)} + \boldsymbol{\zeta} \tag{2}$$

where the matrices $\mathbf{B}^{(j)}$ and $\mathbf{B}^{(M)}$ contain the path coefficients interrelating the latent variables and $\boldsymbol{\zeta}$ represents the vector of the error components. The structural model can be rewritten as:

$$\boldsymbol{\xi}^{(j)} = \mathbf{B}\,\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{3}$$

where $\mathbf{B} = (\mathbf{B}^{(j)}|\mathbf{B}^{(M)})$ is the matrix of all path coefficients and $\xi = (\xi^{(j)\prime}|\xi^{(M)\prime})'$ is the vector of all the latent variables. IN PLS Path Modelling two type of measurement models are considered, [22]: the reflective and formative scheme.

In this setting the reflective way has been chosen because of all the manifest variables are considered related to the latent variable by a simple regression model.

In PLS Path Modeling an iterative procedure allows us to estimate the following model parameters: the outer weights w_{pq} and the latent variable scores ξ_q. The estimation procedure is named partial since it solves blocks one at a time by means of alternating single and multiple linear regressions. The path coefficients β_{mj} come afterwards from a regular regression between the estimated latent variable scores.

The estimation of the latent variable scores are obtained alternating the so-called outer and the inner estimations, iterating till convergence. It is important to underline that no formal proof of convergence has been provided until now. As a matter of fact, until now convergence is proved only for path diagram with one or two blocks, [17]. Nevertheless, empirical convergence is always assured.

The procedure starts by choosing arbitrary weights w_{pq}. Then, in the external estimation phase, each latent variable is estimated as a linear combination of its own manifest variables:

$$v_q \propto \sum_{p=1}^{P_q} w_{pq}\mathbf{x}_{pq} = \mathbf{X}_q\mathbf{w}_q \qquad (4)$$

where v_q is the standardized outer estimation of the q-th latent variable ξ_q and the symbol $\propto$ means that the left side of the equation corresponds to the standardized right side.

In the internal estimation phase, each latent variable is estimated by considering its links only with the other adjacent latent variables:

$$\vartheta_q \propto \sum_{q'=1}^{Q'} e_{qq'}\mathbf{v}_q \qquad (5)$$

where ϑ_q is the standardized inner estimation of the q-th latent variable ξ_q and the inner weights $e_{qq'}$ are equal to the signs of the correlations between the q-th latent variable v_q and the $v_{q'}$ connected with v_q.

Once an estimation of the latent variables is obtained, the algorithm goes on by updating the outer weights w_{pq}. In this way, in according with the reflective model, each of w_{pq} are the regression coefficient in the simple regression of the p-th manifest variable of the q-th block x_{pq} on the inner estimate of the q-th latent variable ϑ_q. Since the latent variable score x_{pq} is standardized, the generic outer weight w_{pq} is obtained as:

$$w_{pq} = \mathrm{cov}\left(x_{pq}, \vartheta_q\right) \qquad (6)$$

i.e. as the covariance between each manifest variable and the corresponding inner estimate of the latent variable.

4. The empirical analysis

The data were collected during the summer of 2009 asking 250 managers to fill in a 15 items questionnaire. The software used in this application is XLSTAT. Using PLS we get the outer weights w_{pq} and the correlations between the manifest variables and their latent variables. The correlation coefficients are validated by bootstrap on 100 samples. Fig 3 shows the parameter estimated for the structural model.

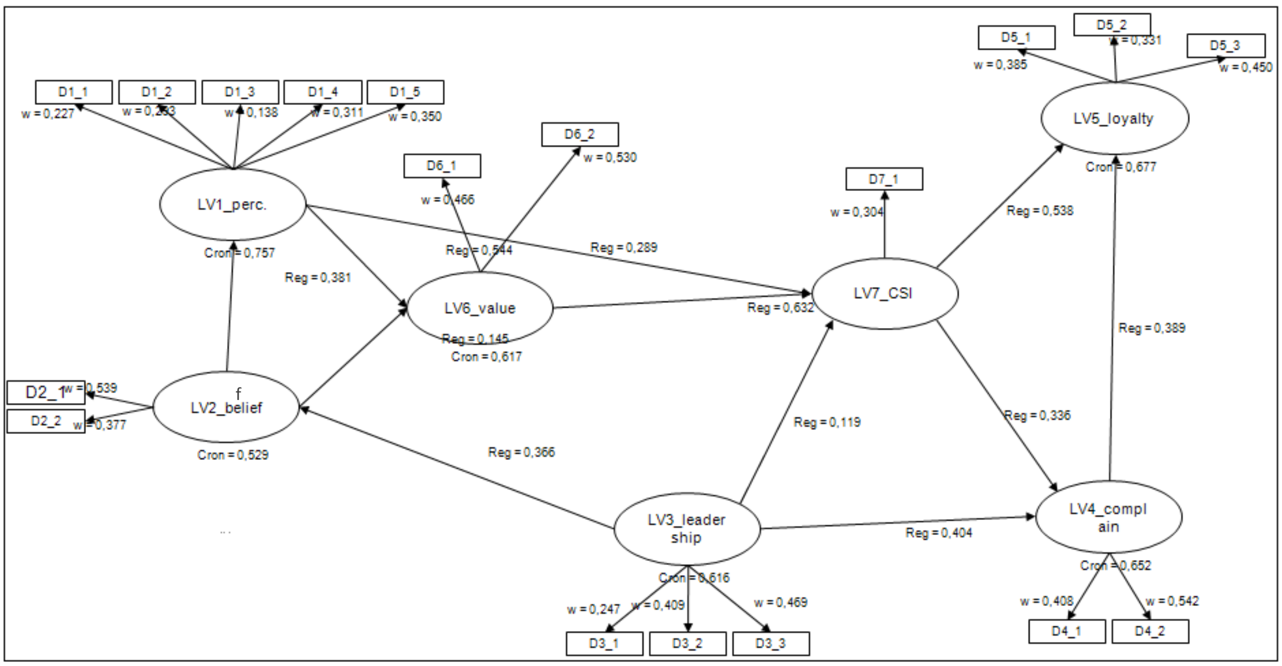

Figure 3. Path model proposed for the network of 250 firms operating in the building retailers

The path coefficients are the standardized regression coefficients. Tab. 2 shows the reliability indexes and the Cronbach's Alpha.

In this application, latent variables are reflective. The single dimensionality of the blocks have been confirmed by the value of Dillon-Goldstein's Rho, which is higher than 0.7 for all the latent variables. Except for the latent variable "Belief" all Cronbach's Alphas show values close to 0.7, confirming the consistency of items.

Table 2. Matrix of the composite reliability indexes

Latent Variable	dimensions	Cronbach's Alpha	D.G.'s Rho	Eigenvalue
LV3_leadership	3	0.616	0.818	2.280
				0.832
				0.485
LV2_belief	2	0.529	0.830	2.354
				0.855
LV1_perc.	5	0.757	0.844	2.695
				1.023
				0.582
				0.406
				0.312
LV6_value	2	0.617	0.844	2.076
				0.746
LV7_CSI	1			
LV4_complain	2	0.652	0.852	2.214
				0.770
LV5_loyalty	3	0.677	0.823	2.182
				0.898
				0.507

Taking into account the correlations between the manifest and the latent variables from Table 3 we can see that all have high values except the following variables: Corr (D1_3, LV1), Corr (D1_3, LV1), Corr (D5_2, LV5) and Corr (D3_1, LV3). However, in agreement with the approach of Martensen [18], the variables LV1, LV6, LV7, LV4 and LV5, are not analyzed since they work well in micro-economic level, as remarked in [13].

Table 3. Correlations between manifest and latent variables

	LV1_perc.	LV2_belief	LV6_value	LV7_CSI	LV5_loyalty	LV4_complain	LV3_leadership
D1_1	**0.679**	0.263	0.359	0.500	0.469	0.404	0.481
D1_2	**0.806**	0.247	0.434	0.582	0.558	0.536	0.749
D1_3	**0.519**	0.200	0.305	0.393	0.385	0.309	0.479
D1_4	**0.718**	0.255	0.475	0.453	0.532	0.508	0.561
D1_5	**0.798**	0.375	0.503	0.756	0.615	0.628	0.604
D2_1	0.317	**0.929**	0.362	0.372	0.454	0.325	0.270
D2_2	0.336	**0.693**	0.175	0.312	0.359	0.273	0.390
D6_1	0.423	0.227	**0.856**	0.684	0.374	0.299	0.374
D6_2	0.600	0.375	**0.848**	0.792	0.667	0.522	0.496
D7_1	0.764	0.414	0.866	**1.000**	0.774	0.609	0.675
D5_1	0.626	0.313	0.433	0.586	**0.816**	0.642	0.541
D5_2	0.473	0.404	0.416	0.428	**0.697**	0.528	0.422
D5_3	0.603	0.437	0.556	0.752	**0.823**	0.524	0.574
D4_1	0.554	0.291	0.319	0.416	0.499	**0.820**	0.486
D4_2	0.638	0.329	0.489	0.611	0.711	**0.897**	0.591
D3_1	0.416	0.342	0.244	0.421	0.518	0.440	**0.524**
D3_2	0.605	0.312	0.371	0.429	0.457	0.473	**0.821**
D3_3	0.747	0.251	0.485	0.667	0.587	0.543	**0.853**

Therefore our attention is focused only on those variables we introduced in place of the item "expectation". In this way, from table 3, it could be possible seen that each manifest variable is more correlated to its own latent variable than to the other latent variables. Therefore the manifest variable D3_1 does not correctly describe its latent variable (corr(Leadership, D3_1)=0,524). This variable should be removed from the model. In fact it is difficult to give a meaningful answer to this item concerning the managerial ability.

The value of multiple R^2, in the case of standardized variables, may be decomposed in terms of the multiple regression coefficients and correlations between the dependent variable and the explanatory ones as follows:

$$R^2 = \sum_j \beta_p corr(y, x_p) \tag{7}$$

This decomposition allows understanding the contribution of each explanatory variable to the prediction of the dependent one and it makes sense only when the regression coefficients and the related correlations have the same sign. For the application proposed in this paper, Table 4 shows that all the variables are significant. In particular "Value" and "Quality Perceived" are the most important variables in the prediction of the customer satisfaction, contributing to, respectively, 64,46% and 26,02% to the R^2.

Table 4. Correlations and path-coefficients for antecedent variables of CSI

	Correlation	Path coefficient	% contribution to R^2	Sig.
LV6_value	0.866	0.632	64.469	0.049
LV1_perc.	0.764	0.289	26.022	0.000
LV3_leadership	0.675	0.119	9.509	0.000

This information is shown more clearly in figure 4 that takes into account the path coefficients

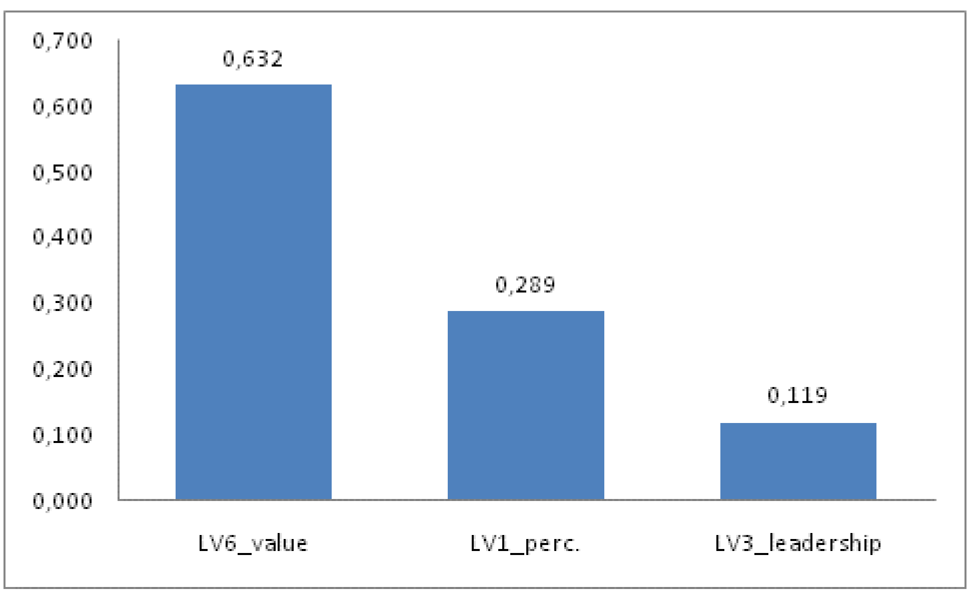

Figure 4. Impact and contribution of latent variables to LV7_CSI

The indices for redundancy, communality and explained variability R^2 are given in Table 5. Redundancy and R^2 may not be computed, of course, for exogenous latent variables (leadership in this case).

Table 5. Values of R^2, average communality of the variables in the analysis

Latent Variable	type	R^2	Communality	Redundancy
LV3_leadership	Exog.		0.559	
LV2_believ	Endog.	0.134	0.672	0.090
LV1_perc.	Endog.	0.145	0.506	0.073
LV6_value	Endog.	0.377	0.726	0.273
LV7_CSI	Endog.	0.848	1.000	0.848
LV4_complain	Endog.	0.460	0.739	0.340
LV5_loyalty	Endog.	0.694	0.610	0.423
Average		0.443	0.606	0.341

It is worth reminding that the average communality is computed as a weighted average of the different communalities with the weights being the number of manifest variables per each block. According to the results in table 5, the GoF index is:

$$GoF = \sqrt{0.443 \times 0.606} = 0.52$$

The index shows that the model seems to fit well the data.

5. Discussion

This study arises from the results of Martensen [18]. Starting from the ACSI and ECSI models helpfully applied to macro levels in comparing national systems, here we proposed an adaptation of ACSI model to a micro economic sector. It was chosen the sector of the firms operating in the building retailers and the occasion was the measure of customer satisfaction into a group of 250 firms.

From the theory developed by Martensen it is possible to see the difficulty of adapting the ACSI model to a micro level due the latent variable “expectation” that seems not fit very well the model. By virtue of this criticism, our proposal, verified in the paper, is to replace the variable defined above with others which provides innovative features. The variables are: “belief” and “leadership”. The first one means the credibility of the communication message delivered through multimedia tools such as, for example, Internet. The second one refers to the ability of the management.

From an empirical point of view, our proposal seems to be valid, being also verified by Cronbach and GOF indexes. So we suggest to adapt the ACSI model, by following our approach, particularly in the case of firms operating as building retailers. A reformulation of the model and the extension of the survey to a wider sample could assess the goodness of the model, so facilitating the performance comparisons, both within and between industries belonging to same economic sector.

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