Some contributions to PLS Path Modeling and a system for the European Customer Satisfaction ([1])

Alcuni contributi al PLS Path Modeling
ed un sistema per la soddisfazione europea dei consumatori

Carlo Lauro, Vincenzo Esposito Vinzi
Dipartimento di Matematica e Statistica
Università "Federico II" di Napoli
carlo.lauro@unina.it, binci@unina.it

Riassunto: La modellizzazione delle misure di customer satisfaction a livello nazionale ed europeo rappresenta un campo di applicazione alquanto nuovo per i modelli ad equazioni strutturali con variabili latenti. In questo lavoro si presenta anzitutto la metodologia dell'approccio PLS per la costruzione dell'indice europeo di customer satisfaction (ECSI). L'adozione di questo approccio nel dominio della customer satisfaction si giustifica a livello teorico per la sua natura predittiva e per una modellizzazione cosiddetta più soffice rispetto a tecniche basate sul criterio della massima verosimiglianza, ed a livello operativo per una maggiore flessibilità nella specificazione del modello. Successivamente, si discutono alcune innovazioni che si stanno apportando all'approccio PLS nell'ambito del progetto ESIS finanziato dalla Commissione Europea con il V Programma Quadro. In particolare, la possibilità di considerare questo approccio come un quadro generale per numerose tecniche di analisi dei dati ne permette un più ampio utilizzo offrendo diverse possibilità per lo sviluppo di tecniche innovative soprattutto nel contesto dell'analisi di tabelle multiple. Infine, si mostra un'applicazione su dati reali relativi alla misurazione della customer satisfaction per una grande azienda privata europea che eroga un servizio pubblico. L'applicazione permette di evidenziare sia i problemi comuni riscontrabili in questo campo con l'approccio classico del modello LISREL che gli strumenti e le modalità di interpretazione dell'approccio PLS.

Keywords: Partial Least Squares (PLS), Structural Equation Modeling, Customer Satisfaction, Multiple Table Analysis.

1. Introduction

The global economy is rapidly changing (e.g. the "new economy") with fundamental shifts in performance and competitiveness between regions, nations and individual economic actors, leading to the necessity for investments in future customer relations. Basing decisions entirely on historic performance indicators is becoming less and less adequate in business as well as within the political spheres. Thus, the development of

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additional indicators, focusing on future potentials and customer stock valuation are becoming increasingly important. The ultimate driving force for any economy is determined by the demands of the people. For that reason, actions focusing on actual user valuation of supplied products (goods and services) are essential, specifically in the new economy sector, where customers change very quickly their minds and are aware of the concurrence.

Performance indicators based on a customer satisfaction index approach and regularly produced have proved important in a number of countries and business environments. The needs for a common European satisfaction index have been raised by various agencies for a number of years and some initiatives have been taken especially in Sweden, Germany and Switzerland. Customer satisfaction measurements constitute an important instrument for such analysis.

To build a satisfaction index, we are faced to the study of structural relations defining causality relations between variables that are not directly observable (*latent* variables) and *manifest* (observed) variables. The latent variables are the facets or components of customers' satisfaction; the manifest variables are customers' answers to the questions concerning their satisfaction. The model linking these variables comes from the theory driving the consumers' decision-making process.

Two statistical approaches may be developed to solve the satisfaction estimation using the model: the PLS approach and the LISREL approach. The PLS solution (see Wold 1982) allows the estimation of latent variables using a system of alternated calculations (Partial Least Squares). The LISREL approach (see Jöreskog 1978) uses the classical estimation method of maximum likelihood. Some situations exist where the LISREL approach is unusable whereas the PLS approach is operational. LISREL algorithm may also have troubles to converge. It is better adapted for a research situation than for operational work. On the other hand, the PLS algorithm is more robust. It can work with a few observations and a lot of variables that may be the case for surveys related to firms with very few big customers. Moreover, data can be continuous, discrete or binary and convergence problems are rare and can be avoided. Finally, the PLS approach allows to robustly estimate the latent variables case values of any model.

The PLS estimation software (LVPLS 1.8, Lohmöller 1987) is only available in a DOS version. It presents important limitations for the number of observations and it is of a very difficult use, completely inadequate for an industrial use. Among the objectives of the ESIS project, there is also the design, development and implementation of a PLS software in conformity with nowadays standards. A first beta-version of this software is used for the application in this paper.

2. PLS Path Modeling

The PLS approach to structural equation modeling (Wold 1966, 1982, Fornell & Cha 1994) studies a system of linear relationships between latent variables by solving blocks (combinations of theoretical constructs and measurements) one at a time (where the term *partial* is derived from) by use of interdependent OLS simple and/or multiple regressions. The data structure of interest to PLS Path Modeling comprises H groups of manifest variables $\mathbf{X} = \{\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_H\}$ representing the observable expressions of H exogenous latent variables $\boldsymbol{\xi} = \{\xi_1, \xi_2, \ldots, \xi_H\}$ and K groups of manifest variables $\mathbf{Y} = \{\mathbf{Y}_1, \mathbf{Y}_2, \ldots, \mathbf{Y}_K\}$ representing the observable expressions of K endogenous latent variables $\boldsymbol{\eta} = \{\boldsymbol{\eta}_1, \boldsymbol{\eta}_2, \ldots, \boldsymbol{\eta}_K\}$. There exist two ways of relating the manifest variables to the respective latent variables: the reflective way and the formative one (Dijkstra 1983). In the case of reflective indicators, typical of classical factor analysis models, the latent constructs give rise to observed variables that covary among them and the model aims at accounting for observed variances or covariances. Reflective manifest variables may be written according to the following outer-directed measurement model:

$$\boldsymbol{X} = \boldsymbol{\Lambda}_X \boldsymbol{\xi} + \boldsymbol{\varepsilon}_X$$
$$\boldsymbol{Y} = \boldsymbol{\Lambda}_Y \boldsymbol{\eta} + \boldsymbol{\varepsilon}_Y$$

where Λ_X and Λ_Y are the matrices of *loadings* relating latent variables to their measures while $\boldsymbol{\varepsilon}_X$ and $\boldsymbol{\varepsilon}_Y$ are zero mean random errors uncorrelated with the latent variables and usually interpreted as measurement errors.

In the case of formative indicators, emergent constructs are combinations of observed indicators and are not designed to account for observed variables. In such a case, the model aims at minimising residuals in structural relationships (explanation of unobserved variances). Formative manifest variable may contribute to the corresponding latent variable according to the following inner-directed measurement model:

$$\boldsymbol{\xi} = \boldsymbol{\pi}_X \boldsymbol{X} + \boldsymbol{\delta}_\xi$$
$$\boldsymbol{\eta} = \boldsymbol{\pi}_Y \boldsymbol{Y} + \boldsymbol{\delta}_\eta$$

where π_X and π_Y are the matrices of the *regression coefficients* while δ_ξ and δ_η are the residuals from regressions. The latter expressions need not to be confused with the so-called *weight relations* defining the estimated latent variables as weighted aggregates of the respective manifest variables such as:

$$\hat{\boldsymbol{\xi}} = \boldsymbol{\omega}_\xi \boldsymbol{X}$$
$$\hat{\boldsymbol{\eta}} = \boldsymbol{\omega}_\eta \boldsymbol{Y}$$

where the weights are determined according to the nature of the measurement model. For reflective indicators, the weights are the loadings after rescaling in a way that the latent variables have a unitary variance. For formative indicators, the weights coincide with the regression coefficients themselves.

Besides the measurement models and the weight relations, the path models with latent variables in PLS modeling consist of a third part related to the structural relations between latent variables as established by substantive theory. The structural model is generally expressed as:

$$\boldsymbol{\eta} = \boldsymbol{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta}$$

where **B** and Γ are the *path coefficients* matrices and ζ is a vector of residuals which is assumed to fulfil the condition $E(\zeta \mid \xi) = 0$.

This assumption is called *predictor specification* and is the only condition imposed in PLS Path Modeling in order to assure desirable estimation properties in the least squares modeling. It implies that the conditional expectation of the endogenous variables with respect to the exogenous ones, and the other endogenous on which they eventually depend, is the systematic part of the relationship and is a linear function of the explanatory variables. Predictor specifications are actually assumed for all regressions run in a PLS Path Modelling; therefore it applies also to both inner-directed and outer-directed measurement models.

As a matter of fact, predictor specification is meant as a *soft* assumption. It avoids the classical i.i.d. assumptions for which the observations need to be jointly ruled by a specified multivariate distribution being also independently distributed. At the same time, it leads to consistent estimates and minimum variance predictions.

This is consistent with the predictive objective of PLS that, differently from covariance structure models, does not aim at minimising the residual covariance matrix by reproducing the observed covariances. Consequently, the residual covariance structure:

$$E\left(\boldsymbol{\varepsilon\varepsilon}'\right) = \boldsymbol{\theta}_{\varepsilon} \quad E\left(\boldsymbol{\delta\delta}'\right) = \boldsymbol{\theta}_{\delta} \quad E\left(\boldsymbol{\zeta\zeta}'\right) = \boldsymbol{\Psi}$$

is not restricted and PLS aims at minimising the trace (variances) of $\boldsymbol{\Psi}$and, in case of reflective indicators, also the trace of $\boldsymbol{\theta}_{\varepsilon}$ while the trace of $\boldsymbol{\theta}_{\delta}$ is minimised in case of formative indicators.

Let us now have a look on the estimation process of the PLS algorithm. The core of this algorithm proceeds in two steps: external estimation of the latent variables ($\mathbf{v}_h$) as weighted aggregates of their own manifest variables ($\mathbf{v}_h \propto \sum_j w_{jh}\mathbf{x}_{jh}$) and internal estimation of the latent variables ($\mathbf{z}_h$) as weighted aggregates of the adjacent latent variables ($\mathbf{z}_h \propto \sum_{h'} e_{hh'}\mathbf{v}_{h'}$). After starting with arbitrary weights (w_{jh}) for the aggregates in the external estimation, the algorithm takes the external estimates as the input of the internal estimation process and iteratively switches between the two processes until convergence between $\mathbf{v}_h$ and $\mathbf{z}_h$ is achieved. Convergence is guaranteed and demonstrated only for the case of 2 blocks but it is practically always encountered also in the case of more than 2 blocks.

Within both internal and external estimation, different estimation options exist in order to better fit the reflective or formative nature of the indicators and the exogenous or endogenous nature of the latent variables.

In particular, in the external estimation process, if the indicators are reflective, the latent variables are similar to principal components of the indicators (Mode A option) by taking the weights w_{jh} equal to the covariances between the specific latent variable and the indicators. Actually, the latent variables case values represent the first PLS regression component (Tenenhaus, 1999) and are the best predictors for the respective indicators. In the case of formative indicators, the regression coefficients are used as weights (Mode B option) so that the latent variables case values represent the multiple regression solution (full-order PLS regression components) and are the best predictands from their own indicators.

The case-values for the latent variables given by the external estimation process are improved as weighted means of those latent variables adjacent in the structural model. The weighting scheme is either the Wold's original centroid one ($e_{hh'}$ = sign of the correlations), or the factorial one proposed by Lohmoller ($e_{hh'}$ = correlation coefficients) or finally the path weighting scheme ($e_{hh'}$ = multiple regression coefficient or correlation coefficient according to, respectively, the endogenous or exogenous role of the latent variables). Practically, these schemes yield results that are not significantly different. With specific reference to the ECSI model, two alternative weighting schemes may be adopted as it is outlined in section 4.

3. Comparing PLS to LISREL

PLS Path Modeling is naturally considered as a competitor of the classical LISREL approach based on maximum likelihood and the assumption of multivariate normality. The literature is full of several discussions on the comparison between the two approaches (the most interesting one in the filed of Customer Satisfaction is in Tenenhaus & Gonzalez 2001). Here, we want to characterise the comparison with respect to the application of both approaches on the ECSI model.
The goal of LISREL (or hard modeling) is actually to provide a statement of causality by seeking to find structurally or functionally invariant parameters, i.e. invariant features of the mechanism generating observable variables) that define how the world of interest to the model at hand works. These parameters are supposed to relate to causes describing the necessary relationships between variables within a closed system.
Unfortunately, most often real data do not meet the requirements for this ideal. PLS (or soft modeling) works on this real data so that its goal needs to be more tempered. Soft modeling aims at identifying predictive links rather than causal ones thus creating the optimal linear predictive relationships among variables. These relationships are interpreted as the best set of predictions available for a given study considering all theoretical, measurement, distributional and practical limitations implicit in the data.
Therefore, the focus of soft modeling is more on empirical data (measurement model) than on theory (structural model). As a matter of fact, LISREL models covariances and is oriented to parameter estimation thus yielding a better structural model because latent variables are space-free while PLS is oriented to prediction of both manifest and latent variables thus yielding a better measurement model because latent variables are constrained in the space of manifest variables.
All these general considerations lead to a preference for PLS Path Modeling when dealing with the ECSI model. Being the theory established and accepted, the aim is to predict the index of customer satisfaction on the basis of the structural model created on substantive theory. PLS is also shown to deal with multicollinearity, skewness of manifest variables, misspecification of inner and outer strcutures in a reasonably robust way (Cassel et al. 1999). All these features are very frequent for the ECSI model and with the kind of ordinal data generated by the related questionnaire.
Some practical considerations arise also from the sample size and the ratio between the sample size and the number of variables. In LISREL, very large sample sizes lead to rejection of the model as having poor fit to the data; on the contrary, very small sample sizes cause the χ^2 reference statistic to be not powerful enough to reject most models. Both cases may occur with the ECSI model according to the different domains of application, e.g. very large sample sizes for surveys run by a new economy company, very small sample sizes for surveys run by a company providing a public service to few big enterprises. With respect to the ratio between cases and variables, for PLS is enough to have more cases than variables in a block and more cases than composite variables. No identification problems occur.

Finally, in our opinion a major problem of LISREL overcome by PLS is the factor indeterminacy. As known, in LISREL there may be several unobservables bearing the same pattern of correlations with observed variables and yet be only weakly or even negatively correlated with each other. The problem is solved in PLS by the weight relations. This is extremely important for the ECSI model as the knowledge of the scores of the different units on the customer satisfaction index is a major demand.

4. Some ESIS Methodological Specifications for PLS Path Modeling

In this paragraph, we outline the most interesting innovations that we are developing and implementing within the framework of the ESIS project. Our interest is focusing on three phases of the analysis: Data Preparation, Model Estimation and Model Validation.
When creating the ECSI model, the manifest variables reflect the questions included in the questionnaire that is designed according to some guidelines but in a specific way for the different company, sectors, industries.
Therefore, before starting treating the data, it is necessary to get a description of the block by checking for its unidimensionality. This makes sense as we deal with reflective indicators. Different criteria may be adopted to accomplish this task, such as the computation of a reliability index (e.g. Cronbach's alpha), or a principal component analysis for interpreting the structure of the eigenvalues and/or the loading plot.
As it is shown in section 6, manifest variables also need to be properly centred and scaled before the analysis is run in order to get latent variables whose values are interpretable as a measure of customer satisfaction. Moreover, these results need to be comparable among companies, sectors, countries, and times of different surveys.
When collecting data from customer satisfaction surveys, it is very often the case that several missing data appear. This situation is being approached either by adopting the NIPALS (Nonlinear Iterative Partial Least Squares) algorithm or by running a PLS regression that implicitly deals with missing data.
The options for the external estimation process are being enriched with respect to the classical Mode A and Mode B discussed above. In particular, as Mode A coincides with taking the first PLS component and Mode B with taking all PLS components, it seems very reasonable to introduce an intermediate PLS Regression Mode where as many components as needed are taken with an improvement in the prediction power of the model and in the flexibility of the model. Furthermore, the estimation phase needs to be generalised to the case of MIMIC variables (i.e. variables with both reflective and formative indicators) that are very often encountered in more general applications to strategic management and organisational theory. Because of the alternating procedure, the MIMIC model is originally hard to deal with in PLS (Fornell and Bookstein 1982) but the problem may be faced by splitting the MIMIC variable into an endogenous and an exogenous one with a known relationship between original and new path coefficients.
With respect to the weight relations shown in section 2, when estimating the latent variables within an ECSI model, Fornell (1992) computes a weighted average of the indicators that differs from the classical aggregate computed in PLS Path Modeling. This mode is very interesting but it actually requires checking for positive coefficients before applying. Moreover, when LISREL is feasible, this mode is applicable directly on either PLS or LISREL latent variables estimates with comparable results.
The Model Validation phase presents several issues. PLS Path Modeling does not optimise any global scalar function so that there is no index that can provide the user

with a global validation of the model (as it is the case with χ^2 and related measures in LISREL). On the contrary, it is required to provide a set of indices to test the different aspects of the predictive relevance of the model with respect to the structural prediction (endogenous variables from exogenous ones), the communality (formative indicators from endogenous variables) and the redundancy (formative indicators from exogenous variables).
Indices for checking the discriminant validity between different latent variables (i.e. their need to measure different concepts) and the monofactorial nature of manifest variables (i.e. their being significantly more correlated with their own latent variables than with the other ones) are also needed for a more complete assessment of the model.
An important role for approaching a general cross-validation measure for the overall prediction relevance of the model may be played by the Stone-Geisser's Q^2 measure based on a blindfolding procedure.
Finally, such a procedure may also provide jackknife standard deviations of parameters. The evaluation of estimates precision is another important issue for which usual significance tests and bootstrap based procedures are currently being tested. The development of bootstrap empirical confidence intervals is multi-faced as it really depends on the estimation modes being adopted and combined in the analysis.

5. A general framework for the analysis of Multiple Tables

In the case of two blocks, several multidimensional data analysis techniques happen to be special cases of PLS Path Modeling obtained by mixing the modes for computing weights on the two sets of variables. For instance, by applying Mode B on one set (retained to be explanatory) and Mode A on the other set (retained to be dependent), the solutions are those of a Redundancy Analysis or Principal Component Analysis onto a Reference Subspace. If Mode B is applied to both sets we get Canonical Correlation Analysis, while PLS Regression is yielded by applying Mode A on both sets.
PLS Path Modeling may be also meant as a general framework for the analysis of multiple tables, i.e. more than two blocks. This is a very promising research framework. In order to perform multiple table analyses with PLS Path Modeling, at first it is necessary to create a supermatrix by stacking the different tables. Different latent variables are then created for each initial table as well as for the supermatrix. Finally, the structural model considers the latent variables related to each initial table as being exogenous of the endogenous latent variable related to the supermatrix. It is clear that now each block of variables is no more unidimensional so that different dimensions of each latent variable are needed. By working on the so-defined model, besides some established relationships, there are several possibilities for developing new methods by exploiting different combinations between modes for estimating weights (A and B) and schemes for computing internal estimates (Centroid, Factorial and Structural).
It is known that some of these combinations yield classical methods such as Generalised Canonical Correlation Analysis (in the sense of both Horst and Carroll), Multiple Factorial Analysis as developed by Pagès, and Maximum Variance Algorithm by Horst. Instead, the pairs (A, Centroid), (A, Factorial), (B, Structural) as well as those related to the newly proposed ones represent open spots for new methods.
As a new result, the authors demonstrate that Multiple Co-Inertia Analysis (ACOM, Chessel & Hanafi 1996) is yielded by mixing Mode A and Centroid Scheme. All these

results relate to symmetrical analyses and become milestones for working in a non symmetrical context.

6. An application of PLS Path Modeling to the ECSI model

The European Customer Satisfaction Index (ECSI) is based on well established theories and approaches in customer behaviour and can be applied to a number of different industries. The general ECSI model contains: a core model, i.e. the traditional latent variables perceived quality, expectations, perceived value, satisfaction index and

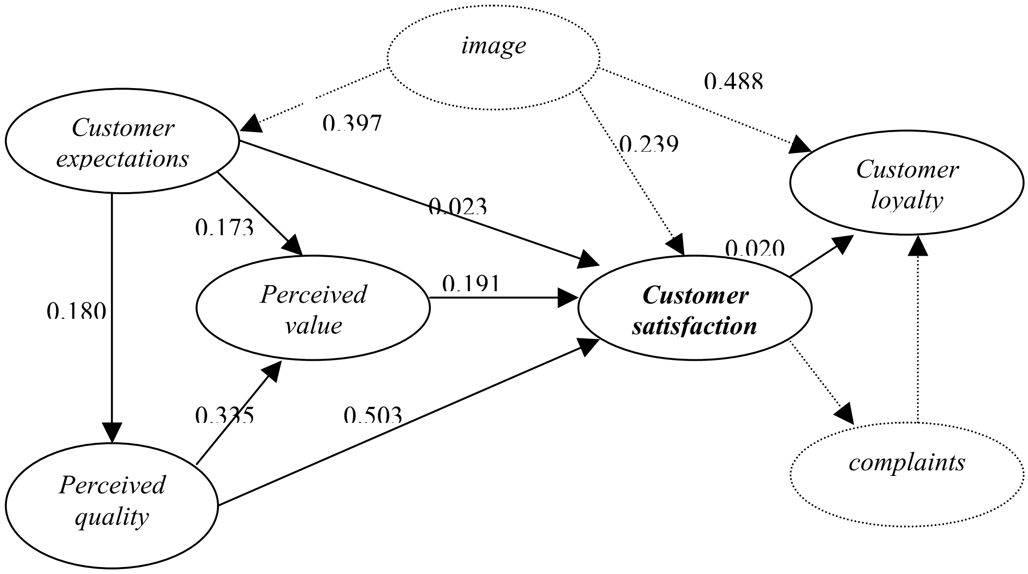

Figure 1: The ECSI model

loyalty; two optional latent variables: image and complaints.

In this application only one of the two optional variables has been considered to be significant: image. A graphical representation of the model can be found in Figure 1.

The variables on the left hand side can be seen as drivers explaining the global customer satisfaction and the right hand performance indicator (loyalty). All represented variables are latent variables: this means they are to be considered as the unobservable phenomenon underlying (and measured by) the observed variables. A set of manifest variables is associated with each latent variables. They are given by the individuals' answers to a questionnaire. All latent variables have a reflective nature.
ECSI model is here applied to data from a major European private firm operating in the public sector. A questionnaire was delivered to a sample of 433 individuals. Respondents were asked to give a rank on a 1-10 scale (1 = "completely disagree", 10 = "completely agree") to a certain number of statements concerning the enterprise. An example of a set of questions related to the Customer Satisfaction latent variable is:

1. I consider myself extremely satisfied of the commercial relationships with this enterprise.
2. I think this enterprise is the best existing one in its sector.
3. I consider myself globally satisfied with technique relationships with this enterprise.

Overall, there are 19 questions related to Perceived Quality, 3 to Customer Satisfaction, 4 to Perceived Vale, 6 to Customer Expectation, 5 to Image and 1 to Loyalty.

As announced in the methodological section, raw variables (x_{jh}) undergo a special transformation. They are originally scaled from 1 to 10 but are transformed into new normalised variables on a 0-100 scale according to the following relationship (Bayol et al., 2000):

$$\tilde{x}_{jh} = \frac{100}{9}\left(x_{jh} - 1\right)$$

The transformed variables are then centred (but not standardised) before performing the analysis. These transformations allow to yield latent variables case values that are interpretable and comparable as measurements of satisfaction.
The standardised regression coefficients relating the latent variables can be read near the arrows linking the pairs of variables. All coefficients are significantly different from 0 at a 5% significance level but the impact of customer expectation on satisfaction (p-value= 0.4872) and the impact of satisfaction on loyalty (p-value=0.7150).
These results are justified by the fact that the company under study provides a public service so that expectation may not be a driving force in determining the satisfaction as well as satisfaction may not significantly influence the loyalty to the brand. On the other side, perceived quality has the strongest impact on customer satisfaction, while loyalty is strongly affected by the brand image.
In general, in PLS Path Modeling the standardised latent variables are calculated as a linear combination of their own manifest variables. In the ECSI model, the latent variables are built as a weighted average of the rescaled manifest variables pertaining to their own block (Fornell 1992). In our examples, Customer Satisfaction is estimated as:

$$\text{ECSI} = \frac{0.028 \times \text{SAT1} + 0.0240 \times \text{SAT2} + 0.220 \times \text{SAT3}}{0.028 + 0.0240 + 0.220}$$

In order to improve the comprehension and interpretability of the relationships among latent variables, a brief analysis of R^2 indices is suggested, especially for Customer Satisfaction. For this latent variable, we get a satisfactory R^2 equal to 0.60 which is the highest value among all predictions in the model (Mean R^2 equal to 0.24). This is a very important result, considering that the model has the main purpose of predicting Customer Satisfaction.
Moreover, considering that the total R^2 can be decomposed in the sum of the path coefficients multiplied by the correlation coefficients of all the explanatory variables, we can decompose the R^2 for Customer Satisfaction among the four explanatory variables (image, perceived quality, customer expectations and perceived value) according to the following decomposition:

$$R^2(\text{ECSI}) = \beta_{\text{image}} \text{ x } corr(\text{ECSI, image}) + \ldots + \beta_{\text{perc. value}} \text{ x } corr(\text{ECSI, perceived value})$$

Each term on the right end side of the previous expression may be interpreted as the contribution of the relative variable to the R^2 for Customer Satisfaction. We get that Perceived Quality has the highest predictive power for ECSI (59.4%) followed by Image (24.88%) and Perceived Value (15.0%).

The same model has been implemented on Amos 4.0 using LISREL maximum likelihood estimation. The results, however, presented a number of problems.
First of all, the complete model has not worked with LISREL. In order to avoid non-identification of the model, another constraint, non confirmed by theory, had to be added. Secondly, one error variance presented a non admissible (negative) value.
All indices pointed out a lack of fit of the model to the data: as an example χ^2 was equal to 2685.836 (656 degrees of freedom) and the RMSEA value showed a confidence interval centred on 0.085 and significantly higher than 0.05.
Modification indices were examined, but the proposed ones were either nonsensical with regards to the underlying theory, or did not cause an appreciable improvement in the model fit.
These results confirm the different objectives and settings of, respectively, the LISREL and the PLS approaches that can be finally considered as possible alternatives more than competing methods.

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