

A MUTIVARIATE STRATEGIC PERSPECTIVE FOR THE EVALUATION OF CUSTOMER SATISFACTION IN GREAT DISTRIBUTION

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Abstract: The author proposes a strategy for the analysis of data from Customer Satisfaction (CS) in Great Distribution. The aim of this paper is to evaluate CS through a comparison of multivariate statistical methodologies.

In this paper the author compares different estimations of Structural Equation Model (SEM) in a case study: evaluation of customer satisfaction in a supermarket. Overall satisfaction is determined by reference to three departments: "Salami and Cheese", "Butchery", "Fruit and Vegetables". Each department is assessed through three aspects: "Assortment", "Staff" and "Offer".

Initially, the links between the different variables are verified through factor analysis and subsequently inserted into a structural equation model. To estimate the model the approach of "maximum likelihood" was used, with LISREL software. Finally, the "Partial Least Squares (PLS) approach was used to confirm the results.

Key words: customer satisfaction; multivariate analysis; great distribution; LISREL

1. Introduction

In the social sciences [14] the study of the evolution of customers' buying behavior and style plays a particularly delicate role.

Companies must adapt to rapid changes. They must take action to meet and even to anticipate expectations. In particular, their aim must be to impress customers with a high level of service in order to strengthen the bond of trust.

For this reason, companies must be aware of the customer's habits and must increase potential loyalty. This can lead to an immediate economic return and a future increase in the total value of the company. In fact, it can survive by relying on the turnover and profitability provided by its customers.

However, the satisfaction-loyalty connection is not always automatic, because of the consumption of goods considered luxuries. There are fringes of customers who, while happy with the product-service received, for new purchases tend to turn to other producers. Thus, satisfaction and loyalty, although closely related, are two different concepts.

In fact, we talk about satisfaction only in cases where those who give an opinion have actually experienced the use of the goods or services purchased. They must be able to give their opinions both in brief and by evaluating tangible and intangible aspects.

Therefore, typical customer satisfaction is real. The potential client can only express an opinion on image, reputation, or repute of the producer of goods or services.

Moreover, particular attention must be paid to customer expectations. These are influenced by a number of factors whose importance varies from individual to individual.

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Consider the difficulty of assessing the impact of personal needs, in turn influenced by past experiences, both direct and indirect.

2. Customer Satisfaction in GD

In recent years, Great Distribution (GD) has a dominant role in the chain transferring products/services to market. In most sectors, the supply of products has increased demand. The critical success of the company tends to depend on the ability to reach the end customer through a more efficient distribution format.

Companies are forced to innovate with new competitive strategies in an attempt to stand out and to gain new market niches [12].

These dynamics are due to continuous economic change, intensifying competition, complexity and articulation of the offer. This explains the growing importance of evaluation of customer satisfaction (CS). In particular, in GD issues of quality are increasingly important, in the sense of the ability to meet customers' implicit and explicit needs.

The evaluation ratings of customers are affected by:

• cultural elements and character traits, such as occupation, educational qualifications, etc.

• psychological factors, such as cognitive and emotional elements

• other factors, such as customer's knowledge of competing firms.

The GD is characterized, therefore, by the presence of an asymmetry of information between the customer receiving the service and the structure that it provides.

For these reasons, in order to improve the quality of services provided, with a view to satisfying customers, GD should pay attention to those factors that will influence the customer's decision to purchase (special promotions, advertising, product placement on shelves, availability of sales staff, etc.).

3. Evaluation of CS through a process-oriented approach

The study of the international context (D'Ambra, L. and Gallo M., 2006) shows that the measurement of satisfaction essentially follows two approaches:

• application-oriented approach of quality models and evaluation of the size characteristics of quality

• oriented approach to evaluate the customer experience in the process of service delivery.

To monitor CS it is necessary to follow the customer through a system that uses the tools dictated by the literature and strictly follow the steps preceding and following data collection (UNI 11098th: 2003).

The author proposes stages of an integrated approach for the evaluation of Customer satisfaction in GD (Table 1).

Step 1	Definition of model, questionnaire, rating scales
Step 2	Universe of reference and sampling plan
Step 3	Data Collection
Step 4	Data quality and pre-treatment
Step 5	Data Analysis
Step 6	Decision support based on results of CS

Table 1. Stages of an integrated approach to process

3.1. Sampling plan

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The sampling adopted is based on two different units of detection:



• Loyal customers. These are customers who make the pilgrimage to the point of sale, fidelity card holders, giving a probabilistic sampling, since the distribution structure has the list of all the loyal customers and can then allocate to each individual the probability of becoming part of the sample. In this case the design may be simple random sampling, stratified by sex or age groups, etc.;

• Occasional customers. These are customers who can be identified by nonprobability sampling, through "face to face" interviews, trying to stratify customers by time and relative abundance (through a survey of presence). An alternative is random sampling in clusters (cluster sampling). The sample is formed by randomly selecting some clusters (bands). In order for the cluster sampling to be effective it is necessary for the clusters not to be too large (for all customers to be interviewed), that their size be as uniform as possible and that the units of which they are composed are the most heterogeneous in terms of type.

3.2. Data quality and pre-treatment

The statistical techniques adopted to validate the questionnaires include:

• Rasch Analysis to verify the scalability of the questionnaire

• Factor Analysis, to evaluate the one-dimensionality

• Use of the coefficient of stability (test-retest), which consists of applying the same tool to the same subject in two subsequent cases, calculating the correlation coefficient between the two sets of scores

• Use of the equivalence factors, which stem from the calculation of the correlation between "parallel forms" of a set of items (a scale or test), administered in a single application (or shortly after). Two or more items (or two or more tests) are called parallel when in measuring the same construct, they are similar in content and/or difficulty.

The coefficients of equivalence most often used are the following:

• Split-half technique. It consists in dividing the questions related to the same concept (of a business process) into two parts and calculating the correlation between the two sets of scores thus obtained. The ratio thus obtained indicates the equivalence of the two halves and the loyalty of the middle test (or scale). This is then corrected using the formula of Spearman-Brown

• Calculation of Cronbach's coefficient alpha. The reliability of Cronbach's coefficient alpha is measured in terms of internal consistency, "it reflects the degree of agreement among multiple measurements of the same theoretical concept obtained at the same time of administration with the same method.

Before analyzing the data, it was decided to pre-treat the data, so as to ensure the quality of information that will be extracted, relating to:

• assessing the quality of the data, responding to the requirements defined by Eurostat documentation in evaluating the quality of statistics produced by the member countries of the European Community concerning the following dimensions: relevance, accuracy, timeliness, transparency, comparability, consistency, completeness

• the treatment of missing data, using deterministic techniques (deductive imputation, imputation by medium)

• quantification of Thurstone which allows for an analysis respecting the ordinal nature of the data through a transformation from ordinal data to linear data (D'Ambra et al, 2001, 2002).

4. Structural Equation Model

For the detection of CS, following a process-oriented approach, a flexible tool must be used to assess the satisfaction of customers who access the service through different pathways.

The questionnaire should be structured so that:

- it describes all processes and activities related to services
- it stratifies the population into subgroups and items of interest.

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The conceptual model can be achieved through the theoretical construct of the structural equation [4] (Structural Equation Model - SEM) method commonly used in the scientific community.

The objective of this methodology is to provide a simplified representation of real processes, taking into account not only the multiplicity of causes that act on a dependent variable, but also the connections between different causes. One of the main reasons is due to the increasing use of software capable of performing statistical analysis based on both the covariance (LISREL, EQS, Amos, etc.) and the search for components (PLS) [3] [6].

Typically, the study of CS is made through the evaluation of customer-perceived satisfaction with aspects of the service received.

These aspects, latent dimensions of satisfaction (latent variables) are quantified through manifest variables, usually expressed on an ordinal scale of scores. The relationship between manifest variables and latent variables can be formalized through patterns that ensure rigour, firstly, in the process of defining the concept of CS, and subsequently in its measurement. The SEM include a first linear system of equations with unknown coefficients which links a set of (endogenous) variables, not observed by each other, with a second set of (exogenous) variables, that are unobservable and linked to expectations.

This structure is complemented by two other sets of equations linking the endogenous and exogenous variables but others have observed. Each set of equations is disturbed by the presence of accidental errors.

The degree of overall satisfaction is identified with one of the latent variables.

$$\eta = B \eta + \Gamma \xi + \zeta$$
$$X = \Delta^{X} \xi + \delta \quad \text{(b)}$$
$$Y = \Delta^{X} \eta + \varepsilon \quad \text{(c)}$$

where:

 η = vector of m endogenous variables

 ξ = vector of n exogenous variables

 ζ = vector of m error

B, Γ = matrices of structural coefficients (the first, linkages between endogenous variables, and others, linkages between endogenous and exogenous)

 $X,\,\delta$ = vectors to exogenous variables and errors observed

 $\Lambda^{\rm X}$ = matrix of structural coefficients between observed variables and latent variables

 $Y_{r} \epsilon$ = vectors of endogenous variables and the errors observed

 $\Lambda^{\rm Y}$ = matrix of structural coefficients between the observed variables and latent variables

4.1. Factor Analysis

The general concept of factor analysis is responsible for a series of statistical techniques whose ultimate goal is to deliver a set of observed variables in terms of a smaller number of hypothetical variables (latent, in LISREL terminology) called factors [13].

Factor analysis provides two approaches: a confirmatory type and an exploratory one, which will be referred to in the case-study considered.

The confirmatory-type approach assumes that the researcher already has a theoretical model of reference, which plans to submit empirical data to verification, while the in exploratory approach there are no assumptions about the number of factors, the identity of the factors and relationships between factors and manifest variables, so it is necessary to estimate all the parameters λ , but a model of this kind (in which all the possible links between manifest and latent are activated) is not identified, and should any of these be bound (usually zero).

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In a model with correlated factors, as in our case, in the model thus identified the student must have at least one variable for each factor "saturated" solely by that factor, as is clear from the matrix Λ^{x} .

$$\mathbf{\Lambda^{x}} = \begin{bmatrix} \lambda^{x}_{1,1} & 0 & 0 & 0 \\ 0 & \lambda^{x}_{2,2} & 0 & 0 \\ 0 & 0 & \lambda^{x}_{3,3} & 0 \\ 0 & 0 & 0 & \lambda^{x}_{4,4} \\ \lambda^{x}_{5,1} & \lambda^{x}_{5,2} & \lambda^{x}_{5,3} & \lambda^{x}_{5,4} \\ \lambda^{x}_{6,1} & \lambda^{x}_{6,2} & \lambda^{x}_{6,3} & \lambda^{x}_{6,4} \\ \lambda^{x}_{7,1} & \lambda^{x}_{7,2} & \lambda^{x}_{7,3} & \lambda^{x}_{7,4} \\ \lambda^{x}_{8,1} & \lambda^{x}_{8,2} & \lambda^{x}_{8,3} & \lambda^{x}_{8,4} \\ \lambda^{x}_{9,1} & \lambda^{x}_{9,2} & \lambda^{x}_{9,3} & \lambda^{x}_{9,4} \\ \lambda^{x}_{10,1} & \lambda^{x}_{10,2} & \lambda^{x}_{10,3} & \lambda^{x}_{10,4} \\ \lambda^{x}_{11,1} & \lambda^{x}_{11,2} & \lambda^{x}_{11,3} & \lambda^{x}_{11,4} \\ \lambda^{x}_{12,1} & \lambda^{x}_{12,2} & \lambda^{x}_{12,3} & \lambda^{x}_{12,4} \end{bmatrix}$$

4.2. Partial Least Squares

The estimation method Partial Least Squares [15] is an exploratory non-parametric approach, it is an not inferential instrument, so the results are valid only for the sample. This definition shows that one cannot make global statistical tests (the only practicable one, the "bootstrap test", is in fact a resampling test that can measure the significance of a link), the PLS [5] approach is optimized by the variance and covariance structures, and there are no errors (the errors are diagonal matrices). The difference between the LISREL and the PLS methods lies in the estimation of the parameters, which happens through the LISREL maximum likelihood method, optimizing a global function to define a single measure of goodness of fit, while the PLS approach is algorithm based on "fixed points", seeking the points of local minimum, or minimum points referring to each of the latent variables.

5. Evaluation of Customer Satisfaction with an Italian supermarket

The data used was collected in an Italian supermarket, in order to be able to develop, test and validate a system to monitor customer satisfaction and the quality offered, designed to assess the level of overall satisfaction perceived by customers.

5.1. Definition of the variables

The variables considered [1] [7] [9] are broadly sixteen, nine of which are manifest exogenous variables (X), corresponding to the three factors considered (range, staff, offerings) collected for each department, three latent exogenous variables (ξ), corresponding to satisfaction with the meats and cheeses, butchery, fruit and vegetables departments, and a latent endogenous variable (η) corresponding to the overall satisfaction score with the supermarket, which in turn is measured by three manifest endogenous variables (Y) corresponding to the overall satisfaction towards the set of staff and goods offered, taken as a whole (Table 2).



Latent Variables	5	Manifest Variables			
Salami and		Assortment	X ₁		
cheese	ξı	Staff	X ₂		
cheese		Goods Offered	X ₃		
		Assortment	X ₄		
Butchery	ζ2	Staff	X ₅		
		Goods Offered	X,6		
	چع ع	Assortment	X ₇		
Greengrocery		Staff	X ₈		
		Goods Offered	Х,		
	η_1	Assortment	Y ₁		
Customer Satisfaction		Staff	Y ₂		
		Goods Offered	Y ₃		

The data collected is qualitative. Therefore, it was transformed to be treated as quantities by the Thurstone procedure, following these steps:

- calculation of the absolute frequencies
- calculation of the relative frequencies
- calculation of the cumulative relative frequencies
- calculation of the inverse of the standard normal distribution function
- quantification of the new scale.

After having assessed the data is to load the new data quantified in the program LISREL, after defining the correlation matrix, obtained by the data-centered and standardized.

5.2 Cronbach'alfa and Correlation of Item-Scale

The construction of a questionnaire drawn up by the questions, then administered to a sample.

Subsequently, it assesses the internal consistency of the scale.

The internal consistency is used to verify the existence of elements of the scale that are not consistent with the others. The instruments used are the Item-Scale Correlation and the Cronbach' alfa coefficient (Table 3).

Latent Variables		Cronbach'alfa	Manifest Variables		Item-Scale Correlation
		0,7	Assortment	X 1	0,54
Slami and	ξ1		Staff	X ₂	0,55
cheese	51		Goods Offered	X ₃	0,46
	برجع	0,75	Assortment	X ₄	0,64
Butchery			Staff	X ₅	0,53
buichery			Goods Offered	X ₆	0,56
	<u>بر</u> ع	0,82	Assortment	X ₇	0,69
Greengrocery			Staff	X ₈	0,63
Greengrocery			Goods Offered	X ₉	0,74
	η	0,76	Assortment	Y ₁	0,59
Customer			Staff	Y ₂	0,59
Satisfaction			Goods Offered	Y ₃	0,59

Table 3. Internal consistency of the scales



The α coefficients measured lead to the scale being accepted. In fact, they exceeded the acceptance limit of 0.7. The values obtained, all tending to 1, showing a good degree of correlation. Therefore, it was not necessary to remove any items of the scale.

Using the matrix above and the data loaded into LISREL, the measurement model was developed.

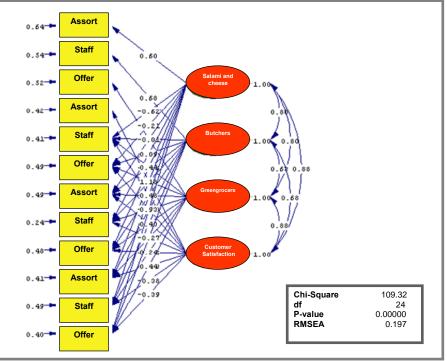


Figure 1. Initial Path Diagram of Factor Analysis

Figure 1 shows that there are many non-significant links, highlighted by the values of the T-value. Consequently, those links were removed, equaling zero so that LISREL does not estimate them. This was followed by the activation of the links suggested by the software through the indices of change and on the basis of "common sense" (by placing the parameters that are to be released in the matrix corresponding to 1).

These operations led us to the definition of the following model, depicted in the second path diagram of Figure 2.

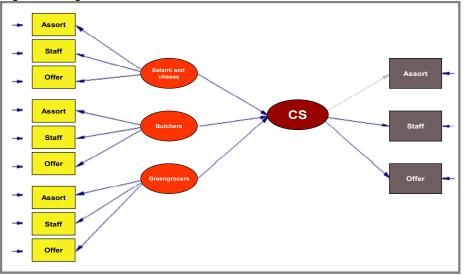


Figure 2. Final Path Diagram of Factorial Analysis



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The model has a Chi-square equal to 105.17 with 45 degrees of freedom, the P-value equal to 0.00000 and does not accept the null hypothesis (H_0 : Σ -S=0), since it falls in the rejection area.

Therefore, we reject the model and nothing can be done to improve it.

The Factor analysis presented does not give useful indications about the possible relationships between the manifest variables and factors.

5.3. Definition of the Model

Progressing in the analysis of the model [8] [10], not being able to use the results obtained from factor analysis, we assumed a theoretical model as presented in Figure 3:

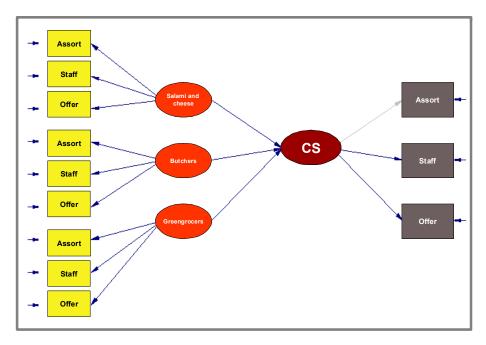


Figure 3. Conceptual Diagram

The model shown has nine manifest exogenous variables, X_n (assortment, staff, offer) underlying three latent exogenous variables:

• ξ_1 , satisfaction department "Salami and cheese"

- ξ_2 , satisfaction department "Butchery"
- ξ_3 , satisfaction department "Greengrocery".

Exogenous variables, through the links of causation, express a latent endogenous variable η (Customer Satisfaction) measured by three manifest endogenous variables Y_n .

The starting point is that this model starts from the idea that the overall satisfaction in a supermarket may depend on the satisfaction with the three departments that comprise it.

The LISREL model is summarized by three basic equations, which for the model in question are expressed by:

• Structural Model, for the causal relationships between endogenous and exogenous variables:

$$\eta_{(1\times1)} = B_{(1\times1)} \eta_{(1\times1)} + \Gamma_{(1\times3)}\xi_{(3\times1)} + \zeta_{(1\times1)}$$
(1)

which in matrix formulation:

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$$[\boldsymbol{\eta}_1] = \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & \gamma_{1,3} \end{bmatrix} \begin{bmatrix} \boldsymbol{\xi}_1 \\ \boldsymbol{\xi}_2 \\ \boldsymbol{\xi}_3 \end{bmatrix} + \begin{bmatrix} \boldsymbol{\zeta}_1 \end{bmatrix}$$

• Endogenous measurement model:

$$\mathbf{Y}_{(3x1)} = \Lambda^{x}_{(3x1)} \,\eta_{(1x1)} + \varepsilon_{(3x1)} \tag{2}$$

which in matrix formulation:

$$\begin{bmatrix} \boldsymbol{y}_1 \\ \boldsymbol{y}_2 \\ \boldsymbol{y}_3 \end{bmatrix} = \begin{bmatrix} \boldsymbol{\lambda}_{1,1}^{\boldsymbol{y}} \\ \boldsymbol{\lambda}_{2,1}^{\boldsymbol{y}} \\ \boldsymbol{\lambda}_{3,1}^{\boldsymbol{y}} \end{bmatrix} [\boldsymbol{\eta}_1] + \begin{bmatrix} \boldsymbol{\varepsilon}_1 \\ \boldsymbol{\varepsilon}_2 \\ \boldsymbol{\varepsilon}_3 \end{bmatrix}$$

• Exogenous measurement model:

$$\mathbf{X}_{(9x1)} = \Lambda^{x}_{(9x3)} \,\xi_{(3x1)} + \delta_{(9x1)} \tag{3}$$

which in matrix formulation:

$\begin{bmatrix} x_1 \end{bmatrix}$		$\lambda_{1,1}^x$	0	0			δ_1	
x_2		$\lambda_{2,1}^x$	0	0			δ_2	
<i>x</i> ₃		$\lambda_{3,1}^x$	0	0			δ_{3}	
<i>x</i> ₄		0	$\lambda_{4,2}^x$	0	$\left[\xi_{1}\right]$		δ_4	
x_5	=	0	$\lambda_{5,2}^x$	0	ξ_2	+	δ_5	
x_6		0	$\lambda_{6,2}^x$	0	_ξ ₃ _		δ_{6}	
<i>x</i> ₇		0	0	$\lambda_{7,3}^{x}$			δ_7	
x_8		0	0	$\lambda_{8,3}^x$	-		δ_8	
x_9		0	0	$\lambda_{9,3}^x$			δ_9	

To complete the formulation of the model, the other four matrices must be specified:

 $\bullet \, \Phi,$ which defines the correlation between the latent exogenous variables, the matrix

 $\bullet \Psi$, which defines the correlation of the errors of the endogenous latent variables

 $\bullet \, \Theta^{\epsilon} \!\!\!\!\!\!,$ which defines the correlation between the errors of measurement of the endogenous model

• Θ^{δ} , which defines the correlation of the errors of the model exogenously.

The four matrices above are all square and symmetrical and the diagonal is the variances of the corresponding variables.

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$$\Theta^{\delta} = \begin{bmatrix} \phi_{1,1} & & \\ \phi_{2,1} & \phi_{2,2} & \\ \phi_{3,1} & \phi_{3,2} & \phi_{3,3} \end{bmatrix} \qquad \Psi = [\psi_{1}] \qquad \Theta^{\varepsilon} = \begin{bmatrix} \theta^{\varepsilon}_{1,1} & & \\ 0 & \theta^{\varepsilon}_{2,2} & & \\ 0 & 0 & \theta^{\delta}_{2,3} & & \\ 0 & 0 & 0 & \theta^{\delta}_{4,4} & & \\ 0 & 0 & 0 & 0 & \theta^{\delta}_{5,5} & & \\ 0 & 0 & 0 & 0 & 0 & \theta^{\delta}_{6,6} & \\ 0 & 0 & 0 & 0 & 0 & 0 & \theta^{\delta}_{6,6} & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta^{\delta}_{8,8} & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta^{\delta}_{9,9} \end{bmatrix}$$

5.4. Results with LISREL

Having identified the eight matrices of the model included in the LISREL software, you get the Path Diagram (Figure 4).

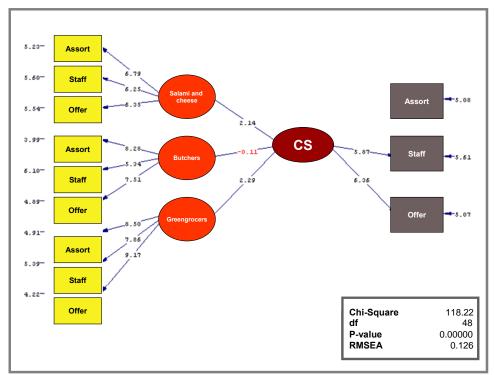


Figure 4. Path Diagram with T-value



The model has a value of chi-square equal to 118.23 with 48 degrees of freedom, a P-value equal to 0.00000, and does not accept the null hypothesis (H_0 : Σ -S=0), since it falls in the rejection area.

Therefore, we reject the model and nothing can be done to improve it.

LISREL through the value of the T-value indicates the existence of a parameter not significantly different from zero, corresponding to the link $Y_{2,1}$.

Removing this link, it is made equal to zero in the corresponding matrix so that the software does not make its estimate. From a conceptual point of view this implies that the latent variable ξ_2 (Butchery) does not directly affect endogenous latent variable η_1 (CS).

Changes made by the new model are presented in Figure 5:

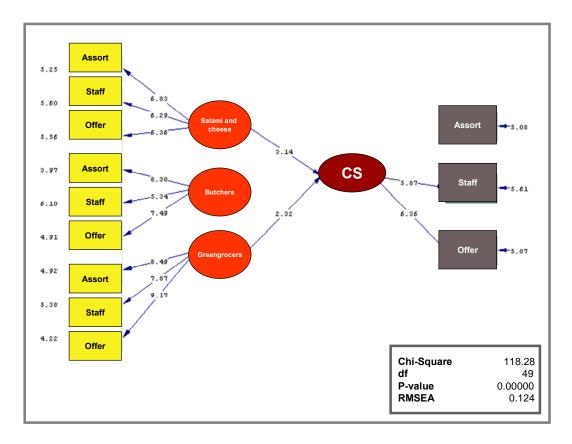


Figure 5. Path Diagram with estimated parameter

The model at this point though slightly better than the previous one (with values of $\chi^2 = 118.28$ and df = 49), is absolutely still to be rejected due to the low P-value (less than 0.10).

Moreover, a conceptual evaluation was done to eliminate the correlations among the latent exogenous variables $\phi_{3,1}$ and $\phi_{3,2}$, keeping only the correlation between satisfaction with "Salami and Cheese" department and the satisfaction with the "Butchery" department ($\phi_{2,1}$). However the resulting model had a value of χ^2 significantly higher than the previous model, which led us to maintain the initial correlations.

Similarly, an improvement to the model analyzed for possible links suggested by LISREL using the indices of change, was not activated because the links are not consistent with an assessment based on "common sense".

Therefore, no other ways of improving the model can be seen.

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5.5. Results with PLS

The model analyzed in this case involves measuring the overall satisfaction with a supermarket (latent variable, CS) using the satisfaction with three other latent variables, "Salami and cheese", "Butchers", "Greengrocers" (Figure 6).

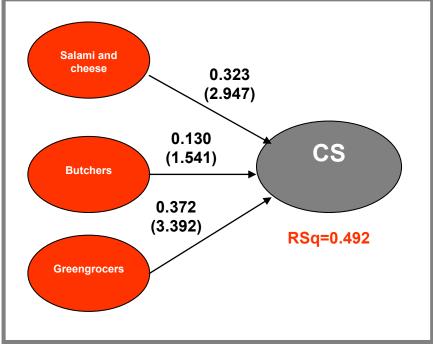


Figura 6. Initial PLS Model

The bootstrap [11] test shows a significant link is not relevant to the relationship between satisfaction with Butchery and customer satisfaction, giving a value of 1.541 (<2). We proceeded to the elimination of this bond and consequently the elimination of the latent variable "Butchery" (Figure 7, Table 4).

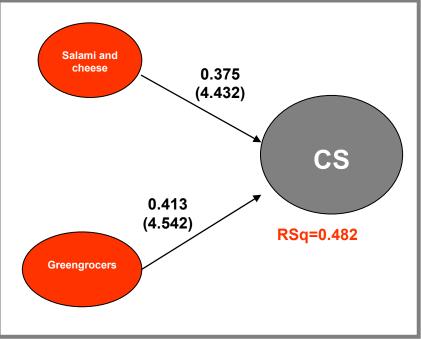


Figure 7. Final PLS Model



Table	4.	Results	with	Bootstrap
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Measurement Mode (weight)						
		Entire Sample Estimate	Mean of Subsamples	Standard Error	T-Statistic	
	Assortment	0.4561	0.4585	0.0890	5.1227	
Salami and	Staff	0.4009	0.3969	0.0824	4.8625	
cheese	Goods Offered	0.4044	0.3981	0.0789	5.1269	
	Assortment	0.3571	0.3524	0.0454	7.8719	
Greengrocery	Staff	0.4114	0.4181	0.0469	8.7654	
	Goods Offered	0.3910	0.3896	0 .0500	7.8133	
Customer Satisfaction	Assortment	0.4253	0.4272	0.0493	8.6348	
	Staff	0.3743	0.3730	0.0419	8.9420	
	Goods Offered	0.4130	0.4157	0.0505	8.1794	

Table 5. Structure Model

Structure Model						
Entire Sample Mean of Standard Estimate Subsamples Error T-Sta						
Salami and cheese ->CS	0.3750	0.3724	0.0846	4.4319		
Greengrocery ->CS	0.4130	0.4241	0.0909	4.5422		

5.6. Comparison of results according to the LISREL and PLS approaches

The model presented a report giving "reflective", which can be expressed by the covariances between the latent variables and manifest variables.

This differs from the reports giving "instructive" in which the variables are used as manifest indicators of latent variables.

Regarding the validation of the model that characterizes the PLS [2] approach is the existence of individual indices of goodness of fit (R^2) is not inferential. Therefore, the results are valid only for the sample. Equally, with the LISREL model there is a global parametric index. Therefore, it is an inferential index and extended to the entire population.

The case study observed a value of \mathbb{R}^2 between 0 and 1, which makes the model acceptable.

Bootstrap analysis of the text referring to this model reveal the values of T-Statistic are all greater than 2, which means that the links are all significant, because their values fall in the rejection of the null hypothesis (H_0 : $\mu = 0$).

Finally, conceptually, analysis of the model shows that the overall satisfaction with a supermarket is not directly dependent on the variable of satisfaction with the "Butchery" department. This confirms the final evaluations obtained with LISREL.



6. Final remarks

The verification of the conceptual model in LISREL showed that Customer Satisfaction with a supermarket is not adequately measured by the variables considered. This means that the satisfaction with one department is not considered a serious effect on overall satisfaction. In particular, the satisfaction with the "butchery" department has no significant impact on "overall satisfaction". For this reason, the corresponding relationship is eliminated.

What led to the falsification of the model is the magnitude of the residual as a whole. It showed that a wide discrepancy between the observed matrix (S) and the matrix Hold (Σ) is not attributable to simple stochastic fluctuations. For this purpose the following were analyzed:

• the Steamleaf Plot for the distribution of residuals, which has a bell shaped curve, considering the "probability sample"

• the Q-plot for the dispersion of the standardized residuals, which shows the straight line interpolating the residuals (near 45° line), making it seem that there is a good model-to-data fit.

The sensitivity of the Chi-square to the sample size (though not particularly large), granted to the analysis of alternative measures of overall adaptation of the model:

• the GFI (goodness of fit index), where the value of the t-statistic is standardized with the maximum value it can reach (it should be between 0 and 1). The reference model is equal to 0.82 (good fit). However, this measure takes no account of degrees of freedom, so that the model is parsimonious

• the AGFI (adjusted goodness of fit index), which is a modified version of the previous year. The value obtained was 0.72 (also between 0 and 1)

• the RMR (root mean squared residuals), which represents a pure average of the squared residuals, which shows a value of 0.073. However, these measures have the disadvantage of not having a statistical distribution. For this reason, we cannot perform significance tests of the model, being valid only for the sample considered.

Having verified the proper fit of the model to data, show that the falsification of the model may be due to an incorrect formulation of the questionnaire, or the fact that other possible variables were not considered.

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