Measuring Quality of Teaching and Learning Performance at University Level
A Proposal to Construct a Global Index

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Abstract

The goal of this paper is the construction of teaching quality indicators, and more general customer satisfaction indexes, at University level. We use Structural Equation Modelling (SEM), which allows to measure latent variables with manifest variables from surveys. The estimation method is Partial Least Squares Path Modelling (PLS-PM) which is the reference with a large number of variables and low sample size. PLS-PM was introduced in the late 70s by Herman Wold. Its actual success is closely related to the success of the customer satisfaction index developed by Claes Fornell. This technique creates aggregations of indices in a global index following a scientific and predictive approach. The proposed methodology is applied to a sample of 900 students and 40 teachers at Universidad Complutense, Madrid, Spain. Different tables and graphs show both the results and the meaning of the obtained global index. Although we apply our methods to a specific university, they can be generalized in order to be used by any other University.

Introduction

Different factors, as the increasing mobility of students, or recent constraints in funding available from governments, mean that universities are facing an unprecedented level of competition in their attempts to attract students and resources. Providers of higher education are under mounting pressure to demonstrate their quality as a measure of social and financial accountability to students, the public, and their governments. These facts have increased the pressure to develop standardised performance indicators to compare institutions at the national and international level.

Our method for the construction of a customer satisfaction index at University level is based on four different steps:

Step 1: we define objective indexes related to University teachers;
Step 2: we define objective indexes related to performance of University teachers;
Step 3: we obtain subjective indexes from a Satisfaction Study carried out on both students and teachers through a questionnaire designed following several structured group interviews;
Step 4: we define an aggregation method to obtain a global quality index.

In this framework, terms “objective” and “subjective” are used in order to distinguish between data obtained from either facts (information obtained from databases provided by the University) or individual perceptions as declared in a survey.

Steps 1 and 2 require collecting information from the institution, while Step 3 needs a survey to be implemented at the institution. On the other hand, Step 4 is the most technical stage of the method, as it requires the construction of our global index. In this step we use Structural Equation Modelling (SEM).

This work is focused on Steps 3 and 4 of the method. The paper is organized as follows: next section presents the method and its theoretical foundations. Then, a description of the procedure used to collect the data is introduced and some results obtained from the application to a sample of 900 students and 40 teachers at Universidad Complutense Madrid are presented. Finally, last section contains some conclusions and a reference for possible future work.

Discussion and hypothesis

Structural Equation Modelling is becoming an important reference in several fields as Marketing, Human Resources Management and Quality, measuring intangible assets as Brand Image, Satisfaction or Human Capital. In general, there exist two different methodologies for this purpose: Covariance Structure Analysis (CSA) and PLS-Path Modelling (PLS-PM). The first one is focused on estimating a covariance matrix, and raw data are not needed to run the model. However, PLS-PM is focus on minimizing errors and maximizing prediction power. This double objective leads to a different aproach with different features of the estimation algorithm. In general terms, CSA is used to confirm theoretical relationships between a small set of variables, while PLS-PM is used in problems without previous theoretical knowledge, a small sample size and large set of variables.

Most of the models applied to daily life problems, or realities, are unknown from the variables relationships point of view. The sample size is usually small for cost constraints and many variables are measured in order to maximize the amount of information, relevant or not for the model. This is the reason why PLS-PM is probably the best statistical approach for measuring customer (professors and students) satisfaction with University Complutense of Madrid. This type of measure is based on surveys, the process to collect them is expensive and then their number tends to be small. Many aspects of the service are measured, so many variables are part of the model, and the relationships between variables are generally unknown and complex.

PLS-Path Modelling

These models are featured by the use of a measurable set of variables, called manifest variables, and a set of non measurable set of variables, called latent variables. The first ones are the questions of the survey, and the last ones are the processes perceived by customers or users of the service, in this case students and professors. Examples of manifest variables are kindness of secretary people, ability of solve your problems,... And examples of latent variables are Secretary Facillities, enrollment process,...

Another important feature of this type of models is the presence of causal relationships between variables, generally established by a path diagram for a better understanding. Each arrow of this path diagram indicates a causal relationship between variables, manifests or latents. Both of them are also represented by different symbols. While latent variables are pictured by a circle or ellypse, a square or rectangle are used for manifest variables.

At this point, it is very important to reach a clear understanding of causality and the relationships contained in a model such as this. The main condition for the existence of a causal relationship could be expressed in these terms; a variable A is cause of B if at any time that A is met then B is also met, and never B is met without the previous meeting of A. There only exist a causal relationship in the sense A→B, since causality is asymmetric.

As illustrated in Figure 1, a path diagram is used to picture a model of causal relationships. Two models are said to compose it; an inner model or structural model and a outer model or measurement model. The first one refers to the latent variables relationships, while the second one refers to manifest variables. This latter one studies the relationships between manifest variables to create an estimation of the latent variables. As it was said, latent variables are not measurable, and they are estimated through a reduced number of manifest variables as a weighted aggregate of them.

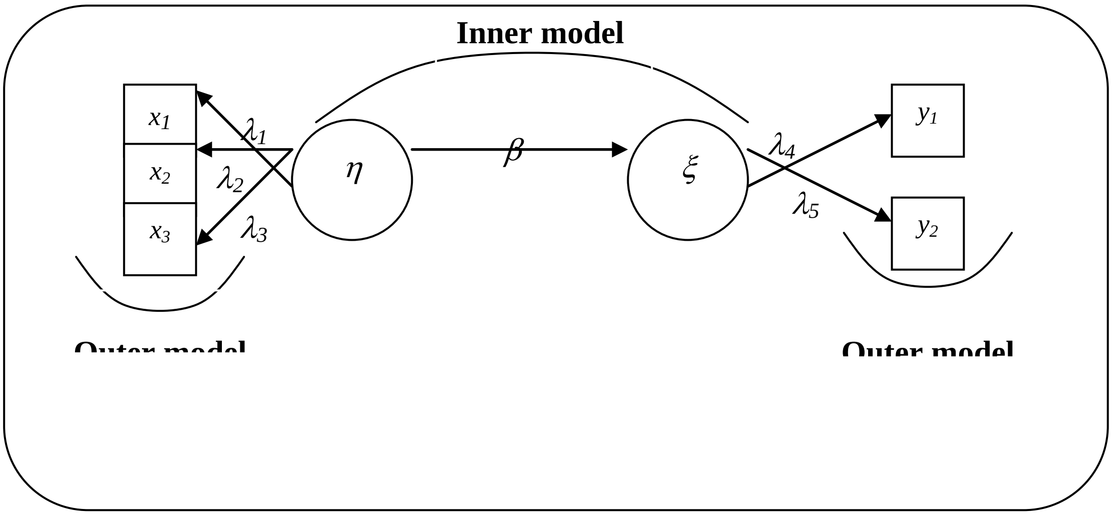

Figure 1: illustration of a path diagram to picture a model of causal relationships in PLS-Path Modelling.

This diagrams are pictured following a set of rules that we introduce below:

manifest variables are represented by a square or rectangle;
latent variables are represented by a circle or ellypse:
error terms of any variable are represented by a square or rectangle, although some statistical packs represent them as circles;
effects of one variable on others are represented by straight arrows from the independent variables to the dependents ones;
greek symbols are used for latent variables (η, ξ).;
latin symbols are used for manifest variables (x, y);
some Greek symbols are used to identify the effects of some varioables on others (β, ϕ, λ, ...).

This path diagramm is transfered to a set of equations with parameters to be estimated. Firstly, the equation that represents the inner model is defined as:

$$\eta = B\eta + \Gamma\xi + \varsigma$$

where:

η represents a vector of endogenous random variables with dimension mx1;
ξ represents a vector of exogenous random variables with dimension nx1;
B represents a coefficients matrix ruling the relationships between the endogenous random variables with dmension mxm;
Γ represents a coefficients matrix ruling the relationships between the exogenous random variables, or said in a different way, the effects of ξ on η. Its simension is mxn;
ζ represents a vector of perturbations or errors.

In this model we have identified exogenous variable with any latent variable not affected by anyone else, and endogenous variable to anyone affected by other.

Once the structural or inner model has been introduced, it is the turn of the measure model or inner model. This one is ruled by two equations; one measuring the relationships between latent endogenous variables and the manifest related to them, and another for the exogenous latent variables. The first one is

$$y = \Lambda_y \eta + \varepsilon$$

where

y is a vector of p observed or manifest variables (px1);
Λy is a coefficient matrix reflecting the relationships between the latent variables and manifest (pxm). This matrix is called loadings matrix;
ε is the error vector (px1).

The second equation of the inner model is the one ruling the relationships between exogenous latent variables and the manifests related to them.

$$x = \Lambda_x \eta + \delta$$

where

x is a vector of p observed variables (qx1);
Λx is a coefficient matriz reflecting the relationships between latent and manifest variables (qxm), also called loadings matrix;
δ is the error vector (qx1).

ACSI Methodology for Customer Satisfaction Sudies

ACSI methodology for customer satisfaction sudies is composed of a set of procedures from the qualitative to the quantitative research. The main features of it are:

-) use of focus groups and in depth interviews to build a questionnire with the relevant aspects preceived by customers or users of the service of an entity;

-) use of rating scale for each manifest variable contained in the questionnaire of ten points, from 1 to 10. This number of even anchors allows us to avoid the mid-point effect;.

PLS-PM is used to create a model to estimate the effects of some variables on others, and for estimation of the weights of manifest variables in each latent variable. Each latent variable is estimated as a weighted aggregate of a set of manifest variables. Fornell´s aproach for this is characterized by a standardized set of weights and transforming the variables from a 1- 10 scale to a 0-100 scale with the following formula:

$$LVi = \left[\frac{\sum_j w_{ij} x_{ij}}{\sum_j w_{ij}} - 1 \right] \times \frac{100}{9}$$

where

wij represents the weight of the j-th manifest variable in the i-th latent variable;
xij represents the j-th manifest variable related to the i-th latent variable;
LVi represents the i-th latent variable.

Application to Professors & Students Satisfaction Study

ACSI methodology has been used to run a study to measure customer satisfaction with the University Complutense of Madrid from the professors and students perpective. This leads to two different models with no primary common units of analysis, but capable to detect the key drivers of customer Satisfaction for both groups.

In order to create these common primary units of analysis, we kept the link between interviewed professor and students, being this latter the ones attending to the lectures of the first one. Then, we have aggregated the students reponse to create a secondary unit of analysis than can be linked to the professors' model. At this point we are able to create a metamodel including the perception of students plus the perceptions of professors. Obviously, the sample size is strongly squeezed and then is when PLS-PM takes an important role to run this metamodel with the achievement of robust estimations.

The main hypothesis is that Professors' satisfaction level impacts onto Students' satisfaction level, but some other relationships, unknown at this present time can be also evaluated. Again PLS-PM is a key technique in this analysis.

Finally, measurement purpose is present in this analysis, and the detection of experiences, processes and patterns to create or to destroy satisfaction are also taken into account.

Procedures for collecting data

Two questionnaires (one for students and another one for Professors) were designed following several structured group interviews: four for students (corresponding to the different years of their degree) and two for Professors (they were divided according to their professional category). The questionnaires obtained had about 100 questions related to different aspects of university life (evaluation, library, secretary, facilities, etc). Figure 2 shows a representation of the model for students, with all blocks considered.

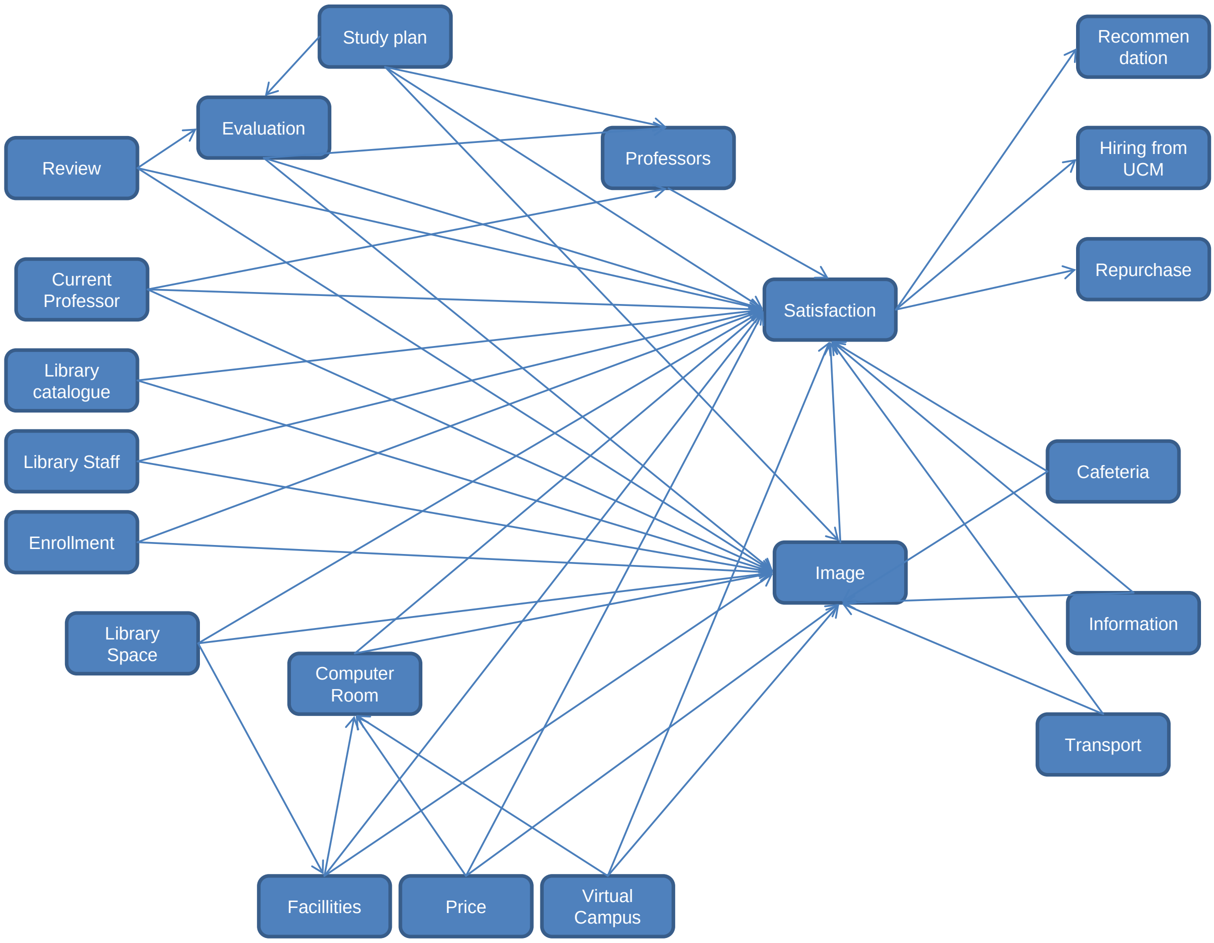

Figure 2: representation of the model for students, with all blocks considered.

As a result, a Satisfaction Study was carried out on both students and Professors. It has be noted that this study and its conclusions can not be considered as a complete study over the whole of the university. We were able to obtain a sample of 900 students and 40 teachers to run the different models, but these samples were only taken from two different Schools. A more exhaustive process shuld be run in order to obtain general conclusions. However, these samples illustrate how the models work and what sort of conclusions can be extracted from them.

Results

Overall, results show how theoretical requirements for this type of models are met in our data, for both students and professors. Table 1 illustrates this point for the students model (similar results have been obtained in the Professor´s case), where results for specific items of each block are listed. The standard loadings of each manifest variable are expected to be greater than 0,707, which means that the communality is higher than 0.5 and shared information between latent and manifest variable is at least half of them. Dillon-Goldstein´s rho (also known as composite reliability) checks whether a block can be considered homogeneous. Usually we assume homogeneity when the value is greater than 0,7. Also, it is important that each latent variable measures only one dimension, so we need to check that the unidimensionality criteria is met. The first manifests correlation matrix eigenvalue must be higher than 1 and the rest lower than 1. As mentioned before, all these requirements are met in our model. Finally, both outer and standard weights are significantly balance for each block of manifest variables. That shows us that the block are built correctly and each manifest variables have reach a role in this model without omitting it. Standard weights are those used to compose the latent variable as a estimation of the real one as weighted aggregate of the manifest variables associated to it.

Latent variable	Manifest variable	Outer weight	Standard weights	Standard loading	Communality	Dimension	Dillon-Goldstein	Eigenvalue
Current Professor								
	P2A	0,1485	0,1213	0,8610	0,7403	8	0,9454	5,4880
	P2B	0,1403	0,1146	0,8727	0,7604			0,6861
	P2C	0,1746	0,1427	0,8733	0,7607			0,5574
	P2D	0,1785	0,1459	0,8948	0,8000			0,4236
	P2E	0,1478	0,1208	0,8759	0,7655			0,2985
	P2F	0,1592	0,1301	0,7816	0,6106			0,2490
	P2G	0,1574	0,1286	0,7090	0,5001			0,1796
	P2H	0,1175	0,0960	0,7468	0,5276			0,1178
Review								
	P4A	0,5778	0,5234	0,9200	0,8373	2	0,9076	1,6617
	P4B	0,5261	0,4766	0,9016	0,8125			0,3383
Evaluation								
	P3A	0,4273	0,3656	0,8686	0,7520	3	0,8940	2,2133
	P3B	0,3799	0,3250	0,8763	0,7639			0,4496
	P3C	0,3617	0,3094	0,8302	0,6845			0,3371
Library space								
	P6A	0,2510	0,2068	0,7993	0,6376	4	0,8955	2,7289
	P6B	0,2961	0,2440	0,8282	0,6849			0,6338
	P6C	0,3257	0,2684	0,7910	0,6259			0,3291
	P6D	0,3409	0,2809	0,8787	0,7720			0,3081
Library staff								
	P7A	0,3597	0,3288	0,9217	0,8348	3	0,9430	2,5399
	P7B	0,3973	0,3632	0,9452	0,8870			0,2961
	P7C	0,3368	0,3079	0,8903	0,7912			0,1640
Enrollment								
	P9A	0,1511	0,1253	0,7322	0,5391	6	0,9298	4,1323
	P9B	0,2237	0,1855	0,8383	0,7015			0,6451
	P9C	0,2061	0,1709	0,8586	0,7360			0,4038
	P9D	0,2098	0,1739	0,8129	0,6576			0,3358
	P9E	0,2197	0,1822	0,8809	0,7744			0,2478
	P9F	0,1957	0,1623	0,8458	0,7139			0,2352
Price								
	P10A	0,4465	0,3889	0,9021	0,8106	3	0,9086	2,3052
	P10B	0,3613	0,3146	0,8960	0,7965			0,4310
	P10C	0,3404	0,2964	0,8261	0,6763			0,2639
Facillities								
	P11A	0,3712	0,3251	0,8713	0,7568	3	0,9111	2,3209
	P11B	0,3636	0,3184	0,8744	0,7637			0,3532
	P11C	0,4071	0,3565	0,8913	0,7939			0,3258
Virtual Campus								
	P12A	0,2819	0,2469	0,8740	0,7631	4	0,9287	3,0617
	P12B	0,2973	0,2604	0,9168	0,8406			0,4267
	P12C	0,3059	0,2679	0,8928	0,7943			0,3090
	P12D	0,2567	0,2248	0,8123	0,6598			0,2025
Secretary								
	P13A	0,1637	0,1394	0,8310	0,6905	6	0,9438	4,4286
	P13B	0,2051	0,1747	0,9242	0,8498			0,5645
	P13C	0,2164	0,1843	0,9189	0,8389			0,4162
	P13D	0,1980	0,1686	0,8225	0,6744			0,2898
	P13E	0,2147	0,1828	0,9033	0,8147			0,1941
	P13F	0,1763	0,1501	0,7348	0,5370			0,1068

Transports								
	P14A	0,4821	0,4564	0,9402	0,8838	2	0,9481	1,8027
	P14B	0,5741	0,5436	0,9569	0,9141			0,1974
Information								
	P16A	0,3540	0,3242	0,9190	0,8420	3	0,9420	2,5323
	P16B	0,3671	0,3363	0,9252	0,8546			0,2590
	P16C	0,3707	0,3395	0,9115	0,8245			0,2087
Cafeteria								
	P17A	0,2965	0,2416	0,7671	0,5866	4	0,8910	2,6895
	P17B	0,2585	0,2107	0,8192	0,6700			0,6076
	P17C	0,2766	0,2254	0,8496	0,7211			0,4927
	P17D	0,3956	0,3224	0,8279	0,6854			0,2102
Professors								
	P1A	0,1887	0,1556	0,8068	0,6477	6	0,9290	4,1164
	P1B	0,2081	0,1716	0,8619	0,7422			0,5958
	P1C	0,2071	0,1708	0,8354	0,6976			0,4492
	P1D	0,2089	0,1723	0,8687	0,7526			0,3827
	P1E	0,1993	0,1643	0,8193	0,6654			0,2359
	P1F	0,2006	0,1654	0,7705	0,5919			0,2200
Study plan								
	P5A	0,5651	0,5130	0,9152	0,8327	2	0,9066	1,6582
	P5B	0,5364	0,4870	0,9056	0,8178			0,3418
Library Catalogue								
	P8A	0,3406	0,2773	0,8300	0,6828	4	0,8905	2,6822
	P8B	0,3308	0,2693	0,8685	0,7457			0,6482
	P8C	0,2856	0,2326	0,7719	0,5924			0,3928
	P8D	0,2711	0,2207	0,7979	0,6344			0,2768
Computer room								
	P15A	0,2513	0,2089	0,8400	0,7021	5	0,9197	3,4837
	P15B	0,2565	0,2131	0,8771	0,7668			0,5879
	P15C	0,2341	0,1946	0,8124	0,6551			0,4214
	P15D	0,2440	0,2028	0,8788	0,7684			0,2692
	P15E	0,2173	0,1806	0,7572	0,5722			0,2378
Image								
	P18A	0,2090	0,1725	0,8177	0,6672	6	0,9298	4,1305
	P18B	0,1981	0,1635	0,8145	0,6627			0,8483
	P18C	0,1880	0,1551	0,8581	0,7350			0,4092
	P18D	0,1917	0,1582	0,8455	0,7098			0,2398
	P18E	0,2161	0,1784	0,8466	0,7138			0,2226
	P18F	0,2087	0,1722	0,7906	0,6220			0,1495
Satisfaction								
	P19A	0,3549	0,3265	0,9112	0,8293	3	0,9442	2,5481
	P19B	0,3402	0,3129	0,9091	0,8253			0,2720
	P19C	0,3920	0,3606	0,9434	0,8873			0,1799
Repurchase								
	P20	1,0000	1,0000	1,0000	1,0000	1		
Recommendation								
	P21	1,0000	1,0000	1,0000	1,0000	1		
Hiring								
	P22	1,0000	1,0000	1,0000	1,0000	1		

Table 1: results for the students model.

Finally, this method allows to assign direct scores to the different latent variables on the general satisfaction index. Table 2 shows these scores. It can be seen how improvement processes could be implemented in areas such as secretary, enrollment, information and evaluation (all with scores below 50). On the other hand, cafeteria place and the current professor attending the class while the survey was taking place have the highest scores (both are near 66.00). General impresion on professors (not only the one atending the class) achieves a score of 49.43, suggesting that students perception of teaching quality is satisfactory.

Latent variable	Score
Cafeteria	65,90
Transports	63,14
Current Professor	62,84
Facillities	56,50
Virtual Campus	56,14
Library space	54,64
Study plan	54,60
Library staff	54,08
Review	53,51
Computer room	51,28
Library Catalogue	49,60
Professors	49,43
Price	40,88
Information	37,80
Evaluation	36,12
Enrollment	29,96
Secretary	19,37
Satisfaction	48,82
Repurchase	55,15
Recommendation	56,53
Hiring	66,12

Table 2: direct scores of latent variables on general satisfaction index.

Conclusions

A customer satisfaction index at University level has been constructed using Structural Equation Modelling (SEM), which allows to measure latent variables with manifest variables from surveys. The estimation method is Partial Least Squares Path Modelling (PLS-PM). The proposed methodology has been applied to a sample of 900 students and 40 teachers. Results show how theoretical requirements for this type of models are met in our data, for both students and professors. Assignation of direct scores to the different latent variables on the general satisfaction index allows to discuss the impact of each block.

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Acknowledgment

The authors acknowledge financial support from the Spanish Ministry of Education, research project EA2009-0016: "Objective and subjective indexes regarding university quality teaching: a method of aggregation of indexes".