ISSN: 2658-8455
Volume 5, Issue 5-1 (2024), pp. 359-371.

Structural equation modeling and student evaluation of teaching: Inputs of the PLS Approach

Modélisation en équations structurelles et l'évaluation de l'enseignement par les étudiants : Apports de l'approche PLS

Mohamed ECH-CHEBANY, ***(PhD Student)***
The Applied Studies and Research Laboratory in Economics (LERASE)
Faculty of Law, Economics and Social Sciences of Agadir,
Ibn Zohr University, Agadir, Morocco

Anas HATTABOU, ***(Full Professor)***
The Applied Studies and Research Laboratory in Economics (LERASE)
Faculty of Law, Economics and Social Sciences of Agadir,
Ibn Zohr University, Agadir, Morocco

Said BRIBICH, ***(Full Professor)***
Faculty of Economics and Management of Guelmim
Ibn Zohr University, Agadir, Morocco

Adil OUATAT, ***(Full Professor)***
Polydisciplinary Faculty of Safi
Cadi Ayyad University of Marrakech, Morocco

Correspondence address :	Faculty of Law, Economics and Social Sciences of Agadir B.P 8658 Cité Dakhla Agadir Tél. 0528217808/0528232817
Disclosure Statement :	Authors are not aware of any findings that might be perceived as affecting the objectivity of this study and they are responsible for any plagiarism in this paper.
Conflict of Interest :	The authors report no conflicts of interest.
Cite this article :	ECH-CHEBANY, M., HATTABOU, A., BRIBICH, S., & OUATAT, A. (2024). Structural equation modeling and student evaluation of teaching: Inputs of the PLS Approach. *International Journal of Accounting, Finance, Auditing, Management and Economics, 5*(6), 359-371. https://doi.org/10.5281/zenodo.11876833
License	**This is an open access article under the CC BY-NC-ND license**

Received: March 23, 2024 *Accepted: June 14, 2024*

Structural Equation Modeling and Student Evaluation of Teaching: Inputs of the PLS Approach

Abstract

Theorists such as Jöreskog (1973), Keesling (1972) and WILEY D.E. (1973) are respectively improved the structural equation models with latent variables in order to examine multiple causal relationships. The two most widely answered procedures in the literature on structural equations are the LISREL method and the PLS method. The PLS method, as Wold (1982) is recommended is based on the use of Partial Least Squares regression techniques for estimating models of structural equations. Indeed, structural equation models are the most suitable for modeling the Student Evaluation of Teaching (SET). The approach (SET) consists of evaluating the quality of the teaching system, based in part on the judgments of students concerning aspects related to the course, and considered to be of primary interest for the educational management of the university. We will concern ourselves in this article to demonstrate how the PLS method would be a relevant method for evaluating the quality of teaching based on student judgments. The PLS approach is suitable for exploratory approaches that do not require a well-founded theory and allow the estimation of partial models, and this is much more consistent with the objective of teaching evaluations by students who are interested in describing the opinions of students.

Keywords: Structural equation modelling, Partial least squares, Student Evaluation of Teaching, Lisrel
JEL Classification : H11, H19
Type du papier : Theoretical Research

Résumé

Des théoriciens tels que Jöreskog (1973), Keesling (1972) et WILEY D.E. (1973) ont respectivement amélioré les modèles d'équations structurelles avec des variables latentes afin d'examiner plusieurs relations causales. Les deux procédures les plus largement discutées dans la littérature sur les équations structurelles sont la méthode LISREL et la méthode PLS. La méthode PLS, comme le recommande Wold (1982), repose sur l'utilisation de techniques de régression des moindres carrés partiels pour estimer des modèles d'équations structurelles. En effet, les modèles d'équations structurelles sont les plus adaptés pour modéliser l'Évaluation de l'Enseignement par les Étudiants (EEE). L'approche (EEE) consiste à évaluer la qualité du système d'enseignement, en se basant en partie sur les jugements des étudiants concernant les aspects liés au cours, et est considérée comme étant d'un intérêt primordial pour la gestion pédagogique de l'université. Nous nous concentrerons dans cet article sur la démonstration de la pertinence de la méthode PLS pour évaluer la qualité de l'enseignement basée sur les jugements des étudiants. L'approche PLS convient aux approches exploratoires qui ne nécessitent pas de théorie bien fondée et permet l'estimation de modèles partiels, ce qui est beaucoup plus conforme à l'objectif des évaluations de l'enseignement par les étudiants qui cherchent à décrire les opinions des étudiants.

Mots clés : Equations structurelles, approche PLS, Evaluation des enseignements par les étudiants, Lisrel.
JEL Classification : H11, H19
Type du papier : Recherche théorique

ISSN: 2658-8455
Volume 5, Issue 5-1 (2024), pp. 359-371.

1. Introduction

Jöreskog (1973), Keesling (1972), and Wiley (1973) pioneered the development of structural equation models featuring latent variables for the investigation of numerous causal connections. Their use was extended to analyses of construct validity (confirmatory factorial), multi-group analyses, and longitudinal studies (Lacroux, 2008). The main interest of these relational models lies in their ability to simultaneously estimate dependence relationships between several independent latent variables and several dependent latent variables.

There are several procedures for estimating structural equation models that differ from each other by the type of algorithm they use. However, the two most popular procedures in the literature on structural equations are the LISREL method and the PLS method.

The LISREL estimation method, born from the work of Karl Jöreskog (1970), is based on the analysis of covariances (Covariance Structural Equation Modeling (CBSEM)) and generally uses the maximum likelihood estimator. Conversely, the PLS approach, introduced by Wold (1982), employs partial least squares regression methods to gauge structural equation models. The principle of this method is based on the analysis of variance (Variance Based Structural Equation Modeling (VBSEM)) and the optimization of the explanatory power of the indicators.

Many educational researchers have started using structural equation modelling; above all, it makes it possible to introduce attitudinal variables into statistical modelling: interactions between student characteristics, personal preferences, affective traits, and motivation levels. Study skills, engagement, teacher support, task orientation, student cohesion, and other factors could help teaching practice (Teo & Khine, 2009). Student evaluation of teaching (EEE), known worldwide as "Student Evaluation of Teaching," is a field of research in education and pedagogical practice that arouses the interest of statisticians. The EEE approach, launched by Italian universities as part of the "National Committee for the Evaluation of the CNVSU University System" program, involves assessing the education system's quality, incorporating students' opinions on aspects deemed crucial for the university's educational administration, as outlined by Balzano and Trinchera in 2011. A questionnaire is generally used to collect this data, and students' judgments are expressed as a score on an ordinal scale. Thus, the main problem posed to statisticians by researchers in this field is the search for a synthetic measure of the quality of teaching, knowing that it is impossible to aggregate individual scores.

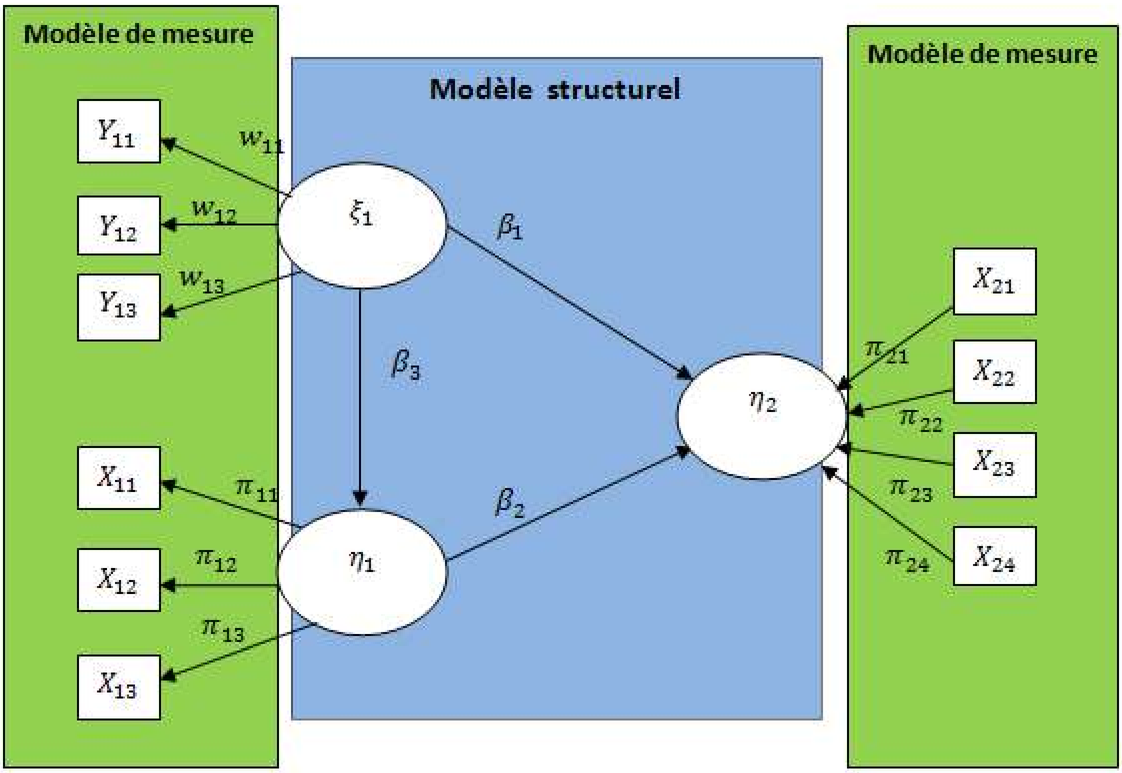
After exposing the principles of the two methods, LSREL and PLS, we will focus in this article on demonstrating how the PLS method would be a relevant method for evaluating the quality of teaching based on student judgments. Indeed, the quality of education and student satisfaction cannot be observed directly but can be measured through several accurate indicators. Therefore, they are assimilated into latent variables, constituting structural models' essential characteristics.

2. Methods for estimating structural equation models with latent variables

2.1 Methods for structural equations with latent variables

After exposing the principles of the two methods, LSREL and PLS, we will focus in this article on demonstrating how the PLS method would be a relevant method for evaluating the quality of teaching based on student judgments. Indeed, the quality of education and student satisfaction cannot be observed directly but can be measured through several accurate indicators. Therefore, they are assimilated into latent variables, constituting structural models' essential characteristics. In structural equation modelling, a latent variable is a variable that is not directly observable and, therefore, cannot be directly measured. On the other hand, a manifest variable can collect a direct measurement. The latent variables are subsequently estimated from the manifest variables by dissociating their share of the common variance (e.g., in Figure 1, the latent variable η_1 is measured by the manifest variables X_11, X_12, and X_13). Structural equation models correspond to a system of equations represented in the form of a directed graph where the nodes represent the manifest variables (X_11, X_12, X_13, etc.) in the form of a square and the latent variables (η_1, η_2, and ξ_1) in the form of a circle. The causal links between variables (β_1, β_2, and β_3) are represented by arrows or arcs (see Figure 1). In these models, each manifest variable is associated with a single latent variable; however, the latent variables can be linked.

Figure 1: Schematic of a structural equation model



Source : Authors

A structural equation model is made up of two types of models: the measurement model (or external model) and the structural model (or internal model) (see Figure 1). The measurement model traces all the relationships between each latent variable and its manifest variables. Thus, the measurement model allows the identification and estimation of latent variables from their manifest variables. On the other hand, the structural model represents all of the causal relationships between the latent variables (also called latent constructs); it thus makes it possible to trace the meaning of the hypotheses constituting the research model to be tested.

The processing of structural equation models is based on four standardized steps (Lacroux, 2008):

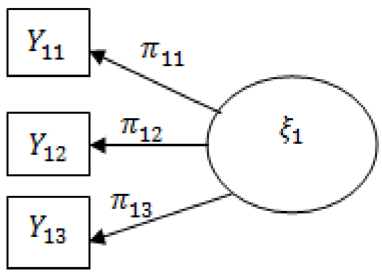
- Model specification: It aims to develop a conceptual model representing the research hypotheses through a relational diagram.
- Identification of the model : This step ensures that obtaining an estimate for all the parameters making up the model is possible.
- Defining measurement scales operationally and gathering and organizing data for subsequent analysis.
- Estimation of the model : It makes it possible to obtain the values of the parameters and examine the quality of fit of the model to the empirical data.

ISSN: 2658-8455
Volume 5, Issue 5-1 (2024), pp. 359-371.

2.2 The specification of structural equation models: Reflective constructs versus formative constructs

Researchers develop conceptual models that summarize their research hypotheses during the specification phase. At this stage, it is undeniable to distinguish between reflective constructs and formative constructs. Any error in specifying the nature of the construct has direct harmful consequences for the conclusions drawn from the research (Fernandes, 2012). The traditional testing theory, led by the Churchill paradigm (1979), supports the idea of a reflective construct. In this type of construct, all indicators are assumed to represent the influence of their build, and thereby, each manifest variable reflects its latent variable. Consequently, every indicator aligns with its method of gauging the phenomenon depicted by the construct, indicating that they all mirror this identical construct. Then, the direction of the causal links operates from the construct to its indicators (e.g., in Figure 2, ξ_1 is a reflective construct, and the arrows (directions of causality) go from the construct ξ_1 to its indicators (Y_11, Y_12, and Y_13). The reflective construct is then considered the common cause shared by all its indicators. Formally, each manifest variable is linked to its latent variable by a linear regression model (e.g., in Figure 2, (Y_11= π_11 ξ_1+ε_11, π_11 represents the loading linking the manifest variable Y_11 to the latent variable ξ_1). All indicators (manifest variables) must be significantly and positively correlated with the above. Therefore, any variation in the construct must be accompanied as faithfully as possible by the variation in all the items of the same construct (Lacroux, 2009). It emerges that in the presence of a reflective construct, the researcher will be led, before estimating his structural equation model, to begin his treatment with the phase of purification (or purification) of the items to ensure the unidimensionality of the construct, its validity, its internal consistency, and the positive sign of the correlations of the indicators with their latent variable. Finally, reflective constructs are practically more adapted to attitude variables (e.g., involvement, feeling of justice, well-being, etc.).

Figure 2: Reflective construct

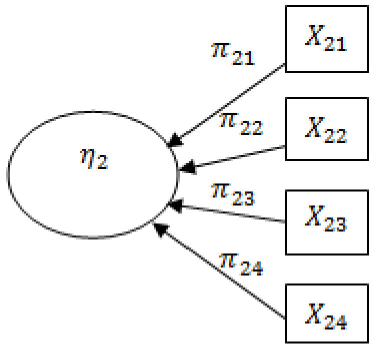


Source : Authors

However, it is possible to end up with models containing one or more formative constructs (Blalock, 1971 ; Bollen & Ting, 2000). A formative construct is a linear combination of indicators (indexes) that are not necessarily correlated, measure theoretically different phenomena, and contribute to forming the latent variable. In this case, and inversely to the reflective construct, the direction of causality goes from the indicators to their latent construct (e.g., in Figure 3, η_2 is a formative construct, the arrows (directions of causality) go from the indicators (X_21, X_22, and X_23) towards the construct η_2). In a formal representation, the latent variable is expressed as a linear combination of the observable variables and an additional random component. For instance, in Figure 3, η_2 is equivalent to π_21, which represents the weight connecting the observable variable (X_ij to the latent variable η_2. Hence, a formative construct, in contrast to a reflective one, can encompass multiple dimensions. Hence, a formative construct, in contrast to a reflective one, can encompass various dimensions.

Consequently, it symbolizes a set of indicators that may not necessarily share a unified theme but must collectively shape the conceptual and empirical significance of the specific construct under consideration. A positive correlation between manifest variables is possible but unnecessary, as in the reflective construct. On a practical level, an example of the formative construct commonly put forward by researchers is the scale measuring the socio-economic status of an individual, which is composed of a combination of four indicators (not necessarily correlated), which are the level of education, annual income, job held, and place of residence (Hauser 1973).

Figure 3 : Formative construct



Source : Authors

In addition to reflective and formative constructs, there is a third type of latent variable called mixed. We then speak of MIMIC mode (Multiple Indicators, Multiple Causes), which is when a construct is composed of both indicators of a reflective and formative nature. This type of latent variable described by Hauser and Goldberger (1971) and Jöreskog and Goldberger (1975) can be interpreted in three different ways: as a single construct with two types of manifest variables, as a combination of exogenous variables influencing a unique reflective construct, and finally as a composite construct which influences two different reflective constructs. However, these configurations are empirically indistinguishable because they lead to the exact estimates. The distinction between reflective and formative constructs is crucial when modelling structural equations. Indeed, poor specification of the nature of the construct inevitably influences the quality of the measurement model, which impacts the validity of the results at the structural model level (Anderson & Gerbing, 1982; Jarvis et al., 2003; McKenzie & al., 2005).

Consequently, the statistical treatment will be different in evaluating the validity and consistency of the measurement scales depending on the nature of the reflective or formative construct. Thus, the classic procedures widely used to validate measurement scales are based on the hypothesis of a positive correlation between the indicators. Therefore, they are appropriate for the evaluation of reflective constructs. Above all, this concerns procedures for verifying the one-dimensionality of constructs and purifying measurement scales. These methods automatically lead to rejecting indicators with a low correlation with others. It's crucial to note that using inappropriate approaches in the case of a formative constraint can have significant consequences. If applied, these approaches can lead to the elimination of items that may be relevant to the research, potentially skewing the results and compromising the validity of the study.

Assessing a formative structure is a unique challenge involving evaluating indicators that depict diverse dimensions without necessarily having a shared overarching theme. This multidimensional construction, by its very nature, presents a complex puzzle. The indices of a

ISSN: 2658-8455
Volume 5, Issue 5-1 (2024), pp. 359-371.

formative construct may or may not be correlated and may even have a negative correlation, rendering internal coherence procedures ineffective. Furthermore, no unanimous methodology exists among researchers for validating this type of construction. To address these unique challenges, Lacroux and Chafik propose using methods introduced by Diamantopoulos and Siguaw, which involve the choice of multiple indices to reduce the variance in the latent variable that remains unaccounted for by its individual components. However, misusing the indexes associated with an idea can diminish this construct's meaning and predictive power.
Finally, incorrect specification at the latent construction level can question the quality of the results obtained from the structural models, thus leading to false conclusions based on the research assumptions (relational structures). According to Jarvis & al. (2003; McKenzie & al. (2005)), errors in specification at the level of latent constructs can lead the researcher, for example, to overestimate structural coefficients and thus to favour relationships when they are insignificant.

2.3 Methods for estimating structural equation models: LISREL versus PLS

2.3.1 LISREL Method

Within the measurement model framework of structural equation models, the employed estimation methods simplify calculating numerical values that characterize the associations between indicators and their latent constructs. Additionally, these methods allow the calculation of structural coefficients, which denote the numerical values of connections between the latent structures in the structural model. Several procedures for estimating structural equation models differ in the type of algorithm they use. Among them are:
- The Lisrel (Linear Structural Relationships) method: this method uses the analysis of the covariance structure and uses the approach of maximum probability; it assumes the multiformity of the data; - the GLS (Generalized Least Squares) method: this method is less sensitive to the non-normalities of data but remains very sensible to the complexity of a model; - the ADF (Asymptotic Distribution Free) and WLS (Weighted Leasta Square) methods: these two methods do not assume data multi normality but instead require a higher sample size (more than 2 500 statistical individuals); - the PLS (Partial Least Square) technique: It is based on variance analysis and based on the approximation of partial squares.

We will limit ourselves to the two most frequently asked procedures in the literature on structural equations: the LISREL method and the PLS method.
Karl Jöreskog (1970) developed the LISREL method, making a notable contribution to statistics and data analysis. It is a type of covariance-based structural equation modelling (CBSEM) that generally uses the estimator of maximum probability. This method, known by various names in literature such as LISREL, structural equation modelling (SEM), covariance Structure Analysis, etc., is a cornerstone of our work. For simplicity, we will refer to it as LISREL. The method allows researchers to construct a theoretical covariance matrix based on the expected correlation coefficients and an observed or empirical matrix from the collected data. The principle of the LISREL method is to iteratively estimate the model parameters, minimizing the difference between the theoretical and empirical matrices.
It is: ∑ the theoretical covariance matrix; S the empirical covalence matrix; η_1, η_2, and ξ_1 the latent variables shown in the model in Figure 1.

$$\text{Eq. 1 :} \quad \eta_2 = \beta_1\xi_1 + \beta_2\eta_1 + \varepsilon_2$$

$$\text{Eq. 2 :} \quad \eta_1 = \beta_3\xi_1 + \varepsilon_1$$

With: β corresponds to the regression coefficient and ε to the error term.
The matrix of the theoretical covariance corresponding to the model described by the two equations (Eq. 1 and Eq. 2) will then be:

$$\sum = \begin{pmatrix} var\xi_1 & & \\ cov(\eta_1\xi_1) & var\eta_1 & \\ cov(\eta_2\xi_1) & cov(\eta_2\eta_1) & var\eta_2 \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & & \\ \sigma_{12} & \sigma_2^2 & \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{pmatrix}$$

Similarly, we can express the covariance between | η |_2 and η_1 as follows:

$$cov(\eta_2\eta_1) = \sigma_{23} = cov(\beta_1\xi_1 + \beta_2\eta_1 + \varepsilon_2, \eta_1) = \beta_1\sigma_{12} + \beta_2\sigma_2^2$$

So, it would be simple to express the theoretical covariance matrix by several equations containing the following parameters: the regression coefficients β, the variances of the independent variables σ^2, the covariances between independent variables σ and finally, the variance of the errors that we will note ψ. A vector will represent all these parameters noted Θ. For the model of structural equations shown in Figure 1, this vector can be written as:

$$\Theta = (\beta_1, \beta_2, \beta_3, \sigma_{12}, \psi_1, \psi_2)$$

Thus, the LISREL procedure is to estimate Θ all by minimizing the residues between the two matrices ∑ (theoretical) and S (empirical), in other words, to make the theoretical matrices as close as possible to the empirical matrix by resorting to the Maximum Likelihood (ML) approach. The probability function to be maximized in our case can be formulated as follows:

$$F_{ML}(\Theta) = \log\left|\sum(\Theta)\right| + tr\left\{S\sum(\Theta) - 1\right\} - log|S| - q$$

With tr is the matrix trace and q is the number of observed variables.

The LISREL method bridges the theoretical matrix of the covariances, derived from a pre-established conceptual model, and the empirical matrix formed from real-world data. This method is crucial in confirming a theory, making it an affirmative approach that necessitates a robust theoretical framework for the research model. Probability function maximization further underscores the need for the researcher to adhere to the multiformity conditions of all indicators, which must be continuous or interval. Therefore, the application of this method is primarily determined by the multiformity of the data, the linearity of the model, the independence of the observations, the one-dimensionality of latent constructs, and a relatively large number of observations (at least 200). Similarly, according to several studies, the two most difficult conditions to meet are generally the normality of the data and the number of observations (sample size). However, the violation of the condition of data normality leads to bias in parameter estimates (especially with a small sample (100 observations), to have a direct effect on the estimation of loadings and structural coefficients, to make the importance of sample size and finally to have an impact on Chi-Two test, which is one of the parameters of model adjustment quality (Lei and Lomax (2005)).

2.3.2 PLS method (Partial Least Squares)

The PLS method, proposed by Wold (1982), is based on using regression techniques in smaller partial squares (Partial Least Squares) to estimate structural equation models. The principle of this method is based on variance analysis (Variance Based Structural Equation Modeling (VBSEM)) and the optimization of the explanatory power of indicators. Thus, the estimation of the parameters will be performed iteratively:

First, the latent variables will be estimated as part of the measurement model by linear combinations of their weighted indicators. Then, the links between the latent constructs will be assessed by multiple regressions within the same constructs to the point where the variance explained of the dependent variable by the independent variables is maximum (see Frame 1).

By analogy with factor analysis, the difference between the LISREL and the PLS methods is in the same order as that between the conventional and principal component analyses (Lacroux

2010). Analysis of main components always allows a solution without considering measurement errors. Thus, the PLS approach avoids all inadmissible solutions and indetermination factors and achieves an acceptable solution. It is used in a purely predictive approach where the main objective is to obtain a prediction of independent variables based on dependent variables.
Unlike the LISREL method, the PLS method does not require the multiformity of variables and adapts to continuous, metric and nominal variables. Similarly, it can be used for reflective and formative constructions. It requires fewer observations, as opposed to the LISREL method, which requires at least a sample of 200 observations (Roussel & al – 2002), the PLS method works with reduced samples even with a complex structural model. Thus, the minimum number of observations required for the estimation with the PLS method must be equal, according to the Chin rule (1998), to 10 times the number of relationships emanating from the central construction of the model, i.e. multiplied by ten the amount of manifest variables linked to the latent construction that is connected with the most manifest variable. This feature is essential in social sciences, where it is generally difficult to work with too large samples.
On the other hand, unlike the LISREL method, which fits well with confirmatory analyses that use an excellent and well-founded theoretical construction, the PLS method is very appropriate in estimating models yet to be established by the theory. In this sense, Jöreskog and Wold (1982), predict that "The method of the maximum probability is theoretically oriented and emphasizes the transition between exploratory and confirmatory analysis. PLS has as its primary objective causal and predictive analysis within the framework of complex models developed on a limited theoretical basis."
Finally, the PLS method appears well suited for partial model testing and exploratory analyses in which it is difficult to make a large sample and have extensively tested measurement scales. (Sosik & al– 2009).
However, despite all its advantages, the PLS approach has several limitations. The failure to take into account measurement errors constitutes the most critical limitation of this approach, this limitation reduces the quality of the model estimate and consequently leads to an underestimation of the structural model (structural coefficients) and an overestimation of the measuring model (factor contributions (loadings)). To address this problem, McDonald (1996), proposes having several items per latent variable and working large samples.
Similarly, unlike the LISREL method, the PLS method does not test so-called non-recursive models because its algorithm is based on multiple regression techniques. Thus, only models with univocal structural relationships are testable with the PLS approach (Jöreskog & Wold – 1982).
Finally, another limit inherent in the PLS approach is the absence of model adjustment indices (fit indices). Indeed, unlike the LISREL method, users of the PLS method do not have adjustment indices that allow the tested model to be adjusted to empirical data. However, this does not mean that the models estimated by the PLS algorithm cannot be evaluated; there is a range of calculations (factor contributions, determination coefficient, and some procedures (bootstrap, jackknife)) to ensure the significance of the estimated coefficients (Lacroux 2010).

3. Relevance of the use of the PLS approach for student teaching evaluation (SET)

Over time, statisticians have developed different statistical methods for analysing and interpreting phenomena in other fields and disciplines. Depending on the field of study, these methods range from descriptive to inferential and multi-varied statistics. Psychometric measurements in education, which are becoming more complex, vigorous, and robust, are one area of study that has resorted to the massive use of statistical methods driven by the development of computer tools that have allowed complex data modelling. One of these methods is modelling in structural equations (Khine 2013). Indeed, many educational researchers have begun to use this technique. Its use allows mainly to introduce of attitude variables in statistical modelling: interactions between student characteristics, personal preferences, emotional traits, motivation levels, learning skills, engagement, support to teachers, task orientation, student cohesion and various other factors that could help teaching practice (Teo & Khine, 2009).

Student Evaluation of Teaching (SET) is a field of research in education and teaching practice that attracts the interest of statisticians. The approach (SET), initiated by Italian universities within the framework of the programme "National Committee for the Evaluation of the University System CNVSU", is to evaluate the quality of the educational system based in part on the judgments of students regarding aspects related to the course, and considered to be of primary interest to the pedagogical management of the university (Balzano et Trinchera 2011). A questionnaire is usually used to collect this data, and students' judgments are expressed as a score on an ordinary scale. Thus, the main problem posed to statisticians by researchers in this field is the search for a synthetic measure of the quality of teaching, knowing that there is the impossibility of aggregating individual scores. Indeed, several studies have attempted to propose a synthetic measure of the quality of education using student evaluations (Aiello and Attanasio (2004), Capursi and Porcu (2001), Ramipichini et al. (2004)).

Structural equation modelling would be a relevant method for evaluating the quality of teaching based on student judgments. Indeed, the quality of education and student satisfaction cannot be directly observed but can be measured through several accurate indicators, which are thus assimilated to latent variables that constitute the essential characteristics of structural models.

As seen above, several techniques can be used to estimate the parameters of a structural equation model, which can be grouped into two different approaches: the LISREL approach and the PLS approach. The LISREL method is based on the search for the best parameters for reconstructing the observed covariance matrix of manifest variables. It uses the estimator of maximum probability that requires the manifesto variable multiformity. Nevertheless, in social science research, particularly in studies to evaluate the quality of education, the assumption of the multiformity of the distribution of manifest variables adversely affects the use of the LISREL method. Indeed, since manifest variables are often student judgments expressed on ordinary scales, they cannot be adequately considered and are unlikely to correspond to the multinormal distribution (Balzano et Trinchera 2011).

Contrasting with other approaches, the PLS method stands out for its reliance on variance analysis, which eliminates the need for the multiformity hypothesis of manifest variables. This unique algorithm empowers researchers to estimate intricate models with multiple variables, even on small samples. It also facilitates the exploration of more homogeneous contexts and the comparison of results. For instance, a PLS analysis could be conducted on separate student groups based on external variables like the program they are enrolled in. The PLS algorithm further enhances its appeal with a two-level weighing system. The structural coefficients reflect the influence of exogenous latent variables on the composite indicator (Interest and satisfaction), while standardized weights represent the weights of simple indicators (variables manifests). Together, they determine the coefficients of the final linear combinations (function aggregation) used to calculate the composite indicator (latent variable score) at the individual level. Beyond these technical aspects, the PLS approach is methodologically suited for exploratory studies that don't necessitate a well-founded theory. It also enables the estimation of partial models, aligning well with the objective of student teaching evaluations, which primarily aim to describe students' opinions.

Given these unique features and practical implications, the PLS approach is clearly the most suitable for student-based teaching evaluation studies. Its variance analysis-based methodology, two-level weighing system, and adaptability to exploratory studies make it a powerful tool for understanding and describing students' opinions. Therefore, we strongly advocate using the PLS approach in this field of research.

4. Conclusion

Several techniques can be used to estimate the parameters of a structural equation model, which can be grouped into two different approaches: the LISREL approach and the PLS approach. The LISREL method is based on the search for the best parameters for reconstructing the observed covariance matrix of manifest variables. It uses the estimator of maximum probability that requires the manifesto variable multiformity. Nevertheless, in social science research, particularly in studies to evaluate the quality of education, the assumption of the multiformity of the distribution of manifest variables adversely affects the use of the LISREL method. Indeed, since manifest variables are often student judgments expressed on ordinary scales, they cannot be adequately considered and are unlikely to correspond to the multinormal distribution. (Balzano et Trinchera 2011).
On the other hand, the PLS approach is based on variance analysis and does not require the multiformity hypothesis of manifest variables. Its algorithm allows us to estimate complex models with multiple variables on small samples, as it also allows us to consider more homogeneous contexts and compare the results; it would be interesting, for example, to perform a PLS analysis for separate groups of students based on external variables such as the program followed. Similarly, the algorithm provides a two-level weighing system. Indeed, the results can be interpreted as follows: structural coefficients represent the impact of exogenous latent variables on the composite indicator (Interest and satisfaction). At the same time, standardized weights are the weights of simple indicators (variables manifests). Together, they define the coefficients of the final linear combinations (function aggregation) to calculate the composite indicator (latent variable score) at the individual level. In addition to all these technical considerations, and methodologically, the PLS approach is adapted to exploratory approaches that do not require a well-founded theory and allow the estimation of partial models; this is much more consistent with the objective of student teaching evaluations that are interesting in describing students' opinions. For these reasons, we prefer the PLS approach for student-based teaching evaluation studies.

References

(1). Aiello, F., Attanasio, M., 2004. How to transform a batch of simple indicators to make up a unique one. Atti Della XLII Riun. Sci. Della Soc. Ital. Stat. Sess. Plenarie E Spec. CLEUP Padova 327–338.
(2). Anderson, J.C., Gerbing, D.W., 1988. Structural equation modeling in practice: A review and recommended two-step approach. Psychol. Bull. 103, 411.
(3). Balzano, S., Trinchera, L., 2011. Structural equation models and student evaluation of teaching: A PLS path modeling study, in: Statistical Methods for the Evaluation of University Systems. Springer, pp. 55–66.
(4). Bennaceur, A., Chafik, K., 2019. Les fondements de l'usage des équations structurelles dans les recherches en sciences de gestion : Cas de l'approche PLS. Rev. Contrô Comptab. L'audit 3.
(5). Blalock, H.M. (Ed.), 1971. Causal models involving unobserved variables in stimulus response situations, in: Causal Models in the Social Sciences. Chicago: Aldine, pp. 335–47.

(6). Bollen, K.A., Ting, K., 2000. A tetrad test for causal indicators. Psychol. Methods 5, 3.
(7). Chin, W.W., 1998. The partial least squares approach to structural equation modeling. Mod. Methods Bus. Res. 295, 295–336.
(8). Churchill Jr, G.A., 1979. A paradigm for developing better measures of marketing constructs. J. Mark. Res. 16, 64–73.
(9). Diamantopoulos, A., Siguaw, J.A., 2006. Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. Br. J. Manag. 17, 263–282.
(10). Fernandes, V., 2012. En quoi l'approche PLS est-elle une méthode a (re)-découvrir pour les chercheurs en management? M N Gement 15, 102–123.
(11). Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., 2017. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). SAGE Publications, Los Angeles.
(12). Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev.
(13). Hauser, R.M., 1972. Disaggregating a social-psychological model of educational attainment. Soc. Sci. Res. 1, 159–188.
(14). Hauser, R.M., Goldberger, A.S., 1971. The treatment of unobservable variables in path analysis. Sociol. Methodol. 3, 81–117.
(15). Jarvis, C.B., MacKenzie, S.B., Podsakoff, P.M., 2003. A critical review of construct indicators and measurement model misspecification in marketing and consumer research. J. Consum. Res. 30, 199–218.
(16). Jöreskog, K.G., 1973. „A general method for estimating a linear structural equation system." u Structural equation models in the social sciences, urednici AS Goldberger i OD Duncan, 85–112, in: Njujork, SAD: Seminar.
(17). Jöreskog, K.G., Goldberger, A.S., 1975. Estimation of a model with multiple indicators and multiple causes of a single latent variable. J. Am. Stat. Assoc. 70, 631–639.
(18). Jöreskog, K.G., Wold, H. (Eds.), 1982. The ML and PLS techniques for modeling with latent variables: Historical and comparative aspects, in: Systems under Indirect Observation. Amsterdam: North-Holland, pp. 263–270.
(19). Keesling, J.W., 1972. Maximum likelihood approaches to causal analysis. Ph Diss. Dep. Educ. Univ. Chic.
(20). Khine, M.S., 2013. Application of structural equation modeling in educational research and practice. Springer.
(21). Lacroux, A., 2009. L'analyse des modèles de relations structurelles par la méthode PLS: une approche émergente dans la recherche quantitative en GRH. XXème Congrès L'AGRH Toulouse Du 9.
(22). Lebrument, N., 2012. Intelligence économique et management stratégique: le cas des pratiques d'intelligence économique des PME. Editions L'Harmattan.
(23). Lei, M., Lomax, R.G., 2005. The effect of varying degrees of nonnormality in structural equation modeling. Struct. Equ. Model. 12, 1–27.
(24). MacKenzie, S.B., Podsakoff, P.M., Jarvis, C.B., 2005. The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. J. Appl. Psychol. 90, 710.
(25). McDonald, R.P., 1996. Path Analysis with Composite Variables. Multivar. Behav. Res. 31, 239–270. https://doi.org/10.1207/s15327906mbr3102_5
(26). Porcu, M., Capursi, V., 2001. La didattica universitaria valutata dagli studenti: un indicatore basato su misure di distanza fra distribuzioni di giudizi, in: Convegno Intermedio Della Società Italiana Di Statistica. pp. 17–20.
(27). Rampichini, C., Grilli, L., Petrucci, A., 2004. Analysis of university course evaluations: from descriptive measures to multilevel models. Stat. Methods Appl. 13, 357–373.

(28). Roussel, P., Durrieu, F., Campoy, E., 2002. et El Akremi A.(2002), Méthodes d'équations structurelles: recherche et applications en gestion. Economica.
(29). Sosik, J.J., Kahai, S.S., Piovoso, M.J., 2009. Silver bullet or voodoo statistics? A primer for using the partial least squares data analytic technique in group and organization research. Group Organ. Manag. 34, 5–36.
(30). Teo, T., Knine, M.S., 2009. Structural equation modeling in educational research: Concepts and applications. Sense Publishers.
(31). WILEY D.E., 1973. IDENTIFICATION PROBLEM FOR STRUCTURAL EQUATION MODELS WITH UNMEASURED VARIABLES. United States of America.
(32). Wold, H., 1982. Soft modeling: the basic design and some extensions. Syst. Indirect Obs. 2, 343.