Chapter 8
Supply Chain Evaluation and Methodologies

8.1 Analysis of Performance Factors

The performance factors studied in this research (i.e., risk factors, regional factors, manufacturing practices) are analyzed from a multivariate perspective to identify their impact on supply chain performance benefits. Before introducing the concept of multivariate analysis, below we present a series of supply chain analysis methodologies reported in Avelar-Sosa et al. (2014), who performed a literature review of around 100 research articles on this matter. According to the authors, common methods and techniques for supply chain study include reverse logistics (RL), analytic hierarchy process (AHP), discriminant analysis (DiA), linear regression (LR), descriptive analysis (DA), case studies (CS), simulations (Si), exploratory analysis (EA), factor analysis (FA), and structural equations (SE), among others. As regards supply chain analysis trends, they include supply chain quality, flexibility, risk, and agility, information, and communication technologies (ICTs), enterprise resource planning (ERP), coordination and trust among supply chain partners, and performance. Table 8.1 summarizes this information.

As Table 8.1 suggests, the wide range of available methods and techniques opens the door to new horizons in supply chain analysis. Even though Avelar-Sosa et al. (2014) do not discuss this in detail, most supply chain evaluation methods and techniques study performance elements and indicators, such as delivery times, costs, customer service, competitiveness, and integration. Similarly, many of the reviewed works rely on multivariate methods, such as LR, FA, SE, and AHP, for evaluating supply chain performance indicators. For instance, even though SE were originally a research tool for the social sciences, their use has exponentially increased in other disciplines, such as industrial engineering, to quantify an issue or research aspect.

Several studies employ multivariate techniques to explore supply chain performance factors. For instance, Ranganathan et al. (2011) explored the role of information and communication technologies and networks on supply chain

L. Avelar-Sosa et al., *Evaluation of Supply Chain Performance*,
Management and Industrial Engineering,
https://doi.org/10.1007/978-3-319-93876-9_8

Table 8.1 Trends in supply chain analysis and methodologies

Areas	AHP	RL	FA	DiA	DA	Si	SCa	SE	EA	LR
ERP	0	0	0	0	0	0	1	3	0	0
Risk	1	0	0	1	2	1	1	0	0	1
Integration	0	0	0	0	1	0	3	2	0	0
Competitiveness	0	0	0	1	1	0	1	0	0	0
Quality	0	0	0	0	0	0	0	1	0	0
TIC	0	0	0	0	2	2	1	0	0	0
Performance	7	2	4	4	25	11	47	27	2	4
Collaboration	0	0	0	0	2	0	1	2	0	1
Coordination	0	0	0	0	1	2	1	0	0	0
Location	0	0	0	1	3	0	1	0	0	1
Flexibility	0	0	0	0	1	0	0	1	0	0
Agility	0	0	0	0	0	0	1	2	0	0
Trust	0	0	1	0	0	0	0	0	0	0

Source Avelar-Sosa et al. (2014)

communication, whereas Swafford et al. (2008) studied the impact of flexible processes, manufacturing, and distribution/logistics on supply chain agility. Likewise, some works have relied on multivariate analysis techniques to analyze the effects of technology on supply chain operations, ERP, and innovation channels. In fact, as shown in Table 8.2, current trends in supply chain performance analysis employ multivariate tools in the study of aspects such as ERP, ICTs, and supply chain coordination, flexibility, and location (Lu et al. 2006; Su and Yang 2010a; Zhang and Dhaliwal 2009; Ranganathan et al. 2011; Su and Yang 2010b; Ramanathan and Gunasekaran 2014; Lu et al. 2007; Kim et al. 2013; Autry et al. 2010; Akkermans et al. 2003).

All the studies discussed above have used multivariate analysis as a research tool in regional contexts. This means that they have managed to consider both internal and external operational activities, and consequently, they have assessed risk factors

Table 8.2 Multivariate methods for supply chain performance analysis

Aspect	Linear regression	Factorial analysis	Structural equations	AHP
Agility	0	0	2	0
Risk	0	0	0	1
Collaboration	1	0	2	0
Quality	0	0	1	0
Flexibility	0	0	1	0
Location	1	1	0	0
ERP	0	0	3	0
Technology adoption	0	0	1	0

and regional elements. In other words, it is possible to assess supply chain performance from a causality approach. The following sections discuss a series of causal analysis examples and define the research methodology adopted in this work.

8.2 Multivariate Analysis Methods

8.2.1 Introduction

Multivariate analysis comprises a set of statistical techniques that simultaneously measure, explain, and predict all the existing relationships between the elements of a database. These relationships can be of three types:

- Dependence relationships
- Interdependence relationships
- Classical relationships

Dependence relationships occur when one or more dependent variables are explained by a set of independent variables, whereas interdependence relationships imply mutual reliance between variables. Finally, classical relationships occur when relationships surpass the monocriteria approach. An important concept in multivariate analysis is causality, which occurs when a phenomenon determines to which extent another phenomenon occurs. Causality is a cause–consequence relationship in which one phenomenon causes, to some extent, another phenomenon (Lévy and Varela 2003).

First-generation multivariate analysis emerged in the early 1970s and initially included techniques such as principal component analysis, factor analysis, discriminant analysis, and multiple regression analysis, among others. First-generation multivariate analysis techniques used to focus on descriptive research, which relied on few statistical inferences and less a priori theoretical knowledge. Consequently, all the social sciences virtually received a dose of empiricism, even though these techniques could not analyze one construct with multiple observed variables in a single step, let alone relate these constructs (Roldán and Cepeda 2013). To address the limitations of the first multivariate analysis techniques, second-generation techniques emerged in the late 1980s. They were named structural equation models and recognized that scientific theory implies both empirical and abstract variables. The purpose of these tools is to link data with theory. Structural equation models combine two traditions, an econometric perspective that focuses on prediction, and the psychometric approach that models concepts as latent or non-observable variables, which in turn are composed of multiple observed and measured variables (i.e., indicators or manifest variables) (Roldán and Cepeda 2013; Williams et al. 2009).

Latent variables represent theoretical concepts, whereas indicators are used as inputs in a statistical analysis that provides evidence on the relationships between latent variables (Williams et al. 2009). Multivariate analyses are important because formal science researchers need to take into account multiple observed variables to understand them better. This implies acknowledging, validating, and assessing the reliability of the observed elements by means of direct measurement instruments. Structural equation models have exponentially evolved in the past 30 years thanks to the increasing use of friendly computer programs that make the estimation tasks much easier thanks to user manual and spreadsheets. Similarly, structural equation models are solid grounds to justify variance estimation in modeled cause–effect relationships.

8.2.1.1 Notion of Causality

Causality comes from the ability of the techniques to confront theoretical propositions about a cause and an effect without manipulating the variables, that is, without rigorously controlled experimental designs. Causality refers to a model's assumption, rather than to a property or consequence of the technique. Many variables tend to move along together, yet the mere statistical association between them is not enough to claim there is causality (Casas 2002). The necessary and sufficient condition of causality can be expressed as follows: Variable A is a cause of Variable B if, and only if, every time A occurs, B follows, but B never follows if A does not occur. Causal relationships occur only in the direction $A \rightarrow B$, since causality is asymmetric. However, it is impossible to distinguish between isolated regularities and a causal relationship. Thus, we can claim that a relationship between two variables is causal when we can rule out the possibility that the relationship is spurious or not causal (Lévy-Mangin and Varela 2006).

In social sciences, causal analysis refers to a set of strategies and techniques for developing causal models to explain phenomena in order to contrast them empirically. The origins of causal analysis date back to path analysis. The goal of a path analysis is to study the effects of some variables, considered as causes, over some other variables, considered as effects. Even though path analysis is widely employed in the social sciences, its popularity has lately risen in other fields and knowledge areas thanks to its versatility and ability to explain dependence and interference between multiple variables. Later in this chapter, we will discuss the concept, implications, and considerations of structural equation analyses. That said, the following section provides a brief description of some of the most common multivariate analysis methods. Even though they differ from structural equations, they possess common characteristics. Therefore, it is important to explicitly state their differences to avoid confusions.

8.2.2 Multiple Linear Regression

Regression analysis aims at estimating the average value of a dependent latent variable with respect to the values of one or more additional variables, known as explanatory variables. In this type of analyses, dependent variables are stochastic, whereas explanatory variables are generally non-stochastic. Linear regression has become increasingly popular thanks to the numerous statistical software programs that rely on it. Moreover, it is a robust process that can be adapted to an infinite number of scientific and business applications (Montgomery et al. 2006).

Multiple linear regression is a statistical technique that can be both descriptive and inferential. From a descriptive approach, multiple linear regression has the following abilities:

- Find the best linear prediction equation.
- Control some factors to evaluate the contribution of some specific variables to a linear model.
- Find structural relationships (causality studies).

The regression model can be visualized as follows:

Consider the following relationship to explain the behavior of a dependent variable (Y) with respect to n independent variables (X_1, X_2, …, X_n).

$$Y = f(X_1, X_2, \ldots, X_n) \tag{8.1}$$

where $f(X_i)$ is an implicit function form.

When this implicit function form cannot be estimated, $f(X_i)$ can be approached as follows:

$$Y = \sum_{i=1}^{n} \beta_{i+1} X_i + e \tag{8.2}$$

For $i = 1, 2, \ldots, n$, where β are function parameters, and e is the error due to the linear approximation of Eq. 8.1.

8.2.2.1 The Constant in Regression Analysis

Unlike the other coefficients in the regression equation, β does not measure changes, but rather indicates the effect measured in dependent variable Y and caused by the variables excluded from the equation and the linear approximation. In mathematical models, the constant is the ordinate intercept, or y-intercept, while in econometric models the interpretation of the constant is different. However, in some cases, as in cost functions, which include fixed costs, the regression constant can be interpreted as the intercept.

8.2.2.2 Coefficient Estimation

So far, we have discussed how coefficients can be interpreted, but we have not addressed how they are estimated. The goal of a regression analysis is to find the best estimation of the model parameters to make a close approximation to the real *Y*. Once all the β parameters are estimated, the residual would be the difference between the observed value of variable *Y* and the value predicted for variable *Y* based on the values estimated for the β parameters.

8.2.2.3 Statistics and Hypotheses Testing

Once the parameters are estimated, a set of statistical analyses are performed to assess the model's fit as well as the usefulness and precision of the estimations. The most common statistical tools for linear regression analyses are the following:

– Coefficient of determination

If all the observations coincided with the regression equation, a model would have the perfect fit. However, this is rarely the case. Since statistical models usually have positive and negative errors (e), it is important to have a measure of how well the observed outcomes are replicated by the model, according to the proportion of total variation of outcomes explained by the model. The coefficient of determination, denoted R^2, is a measure of goodness of fit and can be calculated as follows:

$$R^2 = \frac{\sum_{j=1}^{m}\left(\hat{Y}_j - \bar{Y}\right)^2}{\sum_{j=1}^{m}\left(Y_j - \bar{Y}\right)^2} \tag{8.3}$$

In Eq. 8.3, the numerator is the sum of squares due to regression (SSR), and the denominator stands for the total sum of squares (TSS). The coefficient of determination ranges from 0 to 1. That is from 0 to 100% of the variation in Y_j that is explained by SSR. Even though R^2 is a goodness of fit index, it should not be overused, since it can increase its value when more explained variables are added in the analysis, even though they are not significant.

– Significance of the regression coefficient

It is not enough to know how well a regression line fits the data, or to know the standard error of the estimates. It is equally important to know whether dependent variable *Y* is truly related to independent variable(s) *X*. To this end, we must perform a statistical test to determine whether the coefficients for variables *X* are different from 0.

8.2.3 Path Analysis

Path analysis (PA) can assess the fit of theoretical models that comprise a series of dependence relationships. Additionally, path analysis does not test causality but rather helps select or make inferences between causal hypotheses (Batista and Coenders 2000). PA can be considered as an extension of the multiple regression model. Not only does PA highlight the direct contribution from a set of independent variables, but it also emphasizes on the interaction among predictor variables and their direct influence on dependent variables. PA was originally developed in the early years of the twentieth century by Sewall Wright for phylogenetic studies. Later on, it was introduced to the social sciences thanks to the contributions of de Blalock (1964), Duncan (1966), and Boudon (1965), cited by Pérez et al. (2013). Similarly, PA became increasingly popular among psychology, sociology, economics, political sciences, and ecology studies, among others.

Unlike PA, in which each construct is represented by observed variables, structural equation models measure latent variables using multiple measures for their representation, thereby modeling the measurement error. Latent variables are theoretical constructs that cannot be directly measured, but they are associated with a set of manifest or observed variables. Although manifest variables can be directly measured, it should not be assumed that measurements are an exact reflection of the variable. In other words, random and unpredictable factors can hinder error-free measurements (Weston and Gore 2006; Pérez et al. 2013).

Researchers employing PA perform a series of regressions to analyze relationships between independent and dependent variables; that said, some variables can be both dependent and independent, depending on the relationship that is implied. Similarly, it is important to evaluate the goodness of fit of the model, that is, the extent to which the model represents the relationships between the studied variables. Path coefficients explain the impact of one variable over another variable by decomposing this impact in three blocks or paths: path from the independent variable to the intermediate variable, path from the intermediate variable to the dependent variable, and the rest of the path leading to the final variable. By using path coefficients, it is possible to know the correlations between variables after analyzing the set of effects: direct, indirect, or spurious.

As depicted in Fig. 8.1, PA is represented by diagrams that illustrate hypothetical models. In this sense, it is important to consider the following guidelines to correctly develop diagrams:

- An arrow must be used to indicate the relationship between two variables. The direction of the arrow indicates the direction of the relationship.
- A bidirectional arrow must be used to represent covariance between variables.
- Arrows represent path coefficients that indicate the magnitude of the effects in the relationships between two variables.

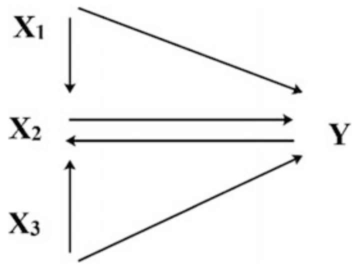

Fig. 8.1 Example of path analysis. *Source* Wright (1971)

- Those variables that receive an influence from other variables are referred to as endogenous variables. Those variables that influence other variables are known as exogenous.
- Observed variables are represented by squares, whereas latent variables are depicted using circles or ellipses.
- Direct effects occur directly from one variable to the other.
- An indirect effect between two variables occurs through one or more mediator variables.

Path models can decompose associations between latent variables through standardized coefficients, which are simply direct effects. On the other hand, indirect effects are estimated by multiplying the path coefficients found between two interrelated variables along the causal line. The statistical significance of any of the given effects can be calculated by dividing the non-standardized coefficients by the standard error. The result is a z value that allows determining the significance of the studied variables (Weston and Gore 2006). Most of the statistics used in PA assume that a multivariate distribution is normal. In this case, a violation to the assumption would be a problem, since it could affect the accuracy of the statistical test, suggesting incorrectly that there is a good fit. Therefore, it is important to conduct some tests before estimating the parameters. Some of these tests include measuring the data at the ordinal or nominal level, measuring collinearity, and using 10–20 cases per parameter and at least 200 observations (Kline 2005).

Structural equation analysis is similar to path analysis since it provides direct and indirect estimations for the observed variables. This property is illustrated in Fig. 8.1. Similarly, there is a wide range of computer programs currently available to support statistical analyses. The study of causal relationships emerged from a technique called multivariable analysis, initially proposed to work with experimental data. Structural equation analysis is a practical and versatile tool; it can effectively and efficiently adapt to all types of research and extract important and detailed information. In conclusion, PA models can have a large explanatory power. Even though they are highly similar to regression, they assume that there exist linear relationships between two observed variables, which implies that one variable has an effect over another (Casas 2002).

8.2.4 Factor Analysis

Factor analysis is a technique for generating structures of theoretical models and hypotheses that can be tested empirically, without previous model specifications or without considering either the number of factors or their relationship (Lévy-Mangin and Varela 2006). Factor analysis, as depicted in Fig. 8.2, is a way to take a mass of data and shrink it into a smaller and more meaningful data set that is also more manageable. A factor is a set of observed variables that have similar response patterns. The number of factors extracted by means of factor analysis is lower than the number of analyzed variables. Once the average values and the standard deviation values are calculated for each construct, it is important to analyze the component matrix to determine whether the items truly belong to the construct wherein they are.

Extracted factors are enough to summarize most of the information contained in original variables. Factor analysis shows which variables are explained by other variables. For instance, in Fig. 8.2, factor 1 (F_1) is explained by variables V_1 and V_2. Moreover, F_1 is related to factors F_2, F_3, and F_4. Similarly, variables V_1 and V_2 have their own measurement errors: e_1 and e_2, respectively. Factor analysis models that describe the correlations from a set of observed variables V_1, V_2 … V_n in terms of a reduced number of common factors, known as latent variables, are represented as a linear equations system as follows (García Ochoa et al. 2017):

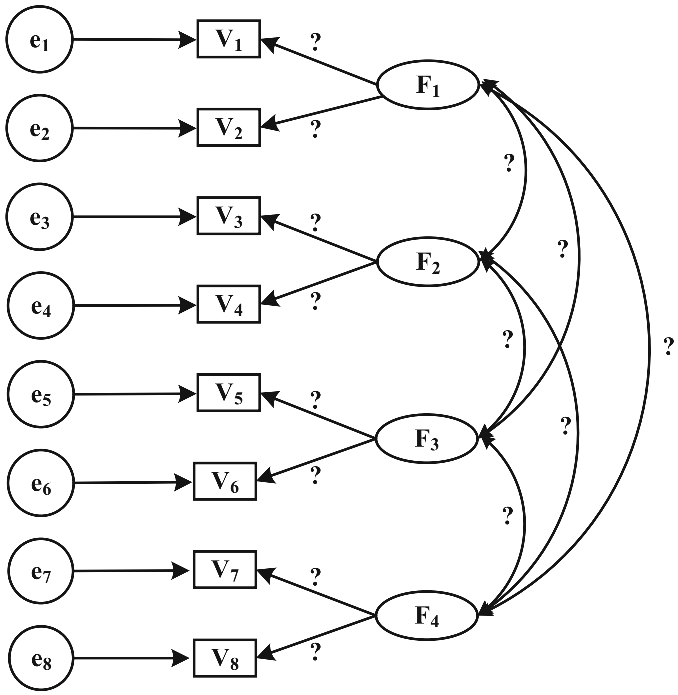

Fig. 8.2 Example of factor analysis. *Source* Prepared by the authors

$$\begin{aligned}
V_1 - \mu_1 &= \lambda_{11}f_1 + \lambda_{12}f_2 + \cdots + \lambda_{1k}f_k + e_1 \\
V_2 - \mu_2 &= \lambda_{21}f_1 + \lambda_{22}f_2 + \cdots + \lambda_{2k}f_k + e_2 \\
&\vdots \\
V_i - \mu_i &= \lambda_{i1}f_1 + \lambda_{i2}f_2 + \cdots + \lambda_{ik}f_k + e_i \\
&\vdots \\
V_p - \mu_p &= \lambda_{p1}f_1 + \lambda_{p2}f_2 + \cdots + \lambda_{pk}f_k + e_p
\end{aligned} \tag{8.4}$$

In Eq. 8.4, V_i represents the observed variables obtained from the data base, although when standardized, they would have zero mean and unit variance for all i = 1, 2, … p. On the other hand, λ_{11}, λ_{12}, …, λ_k represent regression coefficients, usually known as weights or factor loadings; f_1, f_2, …, f_k are the latent common factors, known as latent variables or non-directly observed variables, each one of them with zero mean/unit variance. Finally, residuals e_i are unobserved disturbances from the unique or specific factors. The model only works with interval variables with the same direction (García Ochoa et al. 2017).

8.2.5 Structural Equations (SE)

To describe the relationship between a variable of interest and a predictor variable when it is believed that the latter influences on the former, researchers usually rely on a simple regression model (Silva and Schiattino 2008). However, when in this relationship more than one predictor variable affects the variable of interest, it would be more convenient to propose a multiple linear regression model. Now, let us suppose that the relationship is even more complex: the variable of interest affects variable ***X***, which in turn is influenced by many more variables. Linear regression would not be enough to study this relation, since more equations are necessary. In his work on path analysis, Wright (1932) discussed such complex relationships. Later, Jöreskog (1988) proposed the name structural equations. Structural equation analysis can explain dependence relationships between independent and dependent latent variables. Figure 8.3 shows an example of structural equation analysis, where F_1, F_2, F_3, and F_4 represent independent variables explained by observed variables V_1, V_2, V_3, V_4, etc. The question mark going from F_1 to V_1 represents the percentage that explains this independent variable.

The unknown arrows connecting F_1, F_2, … etc., to variable *Result* indicate the level of importance of the factors associated either positively or negatively to this variable and the relationship between them. When researchers deal with a series of interrelated events, structural equation modeling (SEM) is the most appropriate tool, since it can simultaneously examine dependency relationships. Two of the most important characteristics of SEM are as follows:

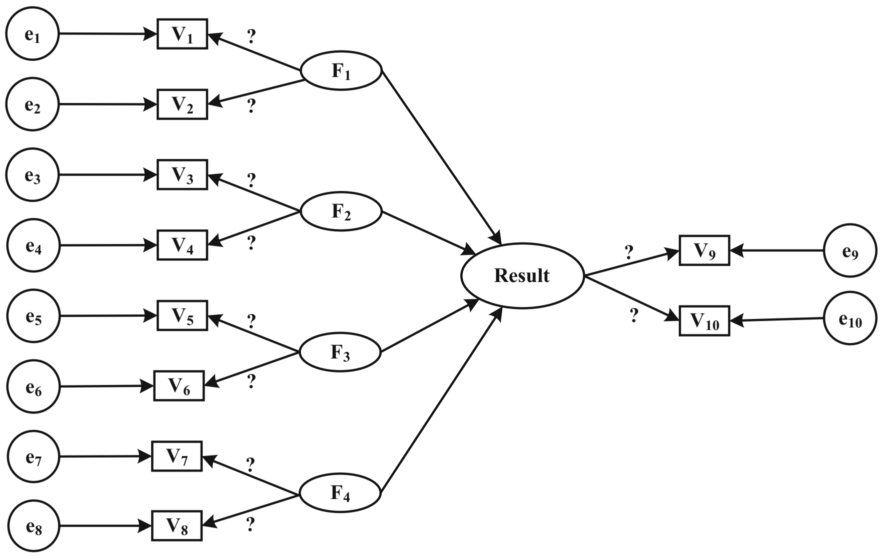

Fig. 8.3 Example of structural equations. *Source* Own

- SEM can estimate multiple relationships and interrelated dependence.
- SEM can represent both unobserved concepts in these relationships and the error measurement in the estimation process.

As depicted in Fig. 8.3, the model allows proposing causal relationships between the variables: That is, some variables cause an effect on others and can transfer these effects to other variables, thereby creating concatenations of variables (Ruiz et al. 2010). Structural equation models are a family of multivariate statistical models that can estimate effects and relationships among multiple variables. Similarly, SEM emerged from the need to rely on more flexible regression models. Structural equation models are less restricted, if compared to regression models, since they can integrate measurement errors in both criterion (dependent) variables and predictor (independent) variables. Likewise, structural equation models can be viewed as factor analysis models that allow for both direct and indirect effects between factors. Mathematically speaking, these models are more difficult to estimate if compared to other multivariate models, such as regression models or factor analysis models.

SEM became popular in 1973 thanks to the appearance of the Linear Structural Relations (LISREL) program (Jöreskog and van Thillo 1973). Later on, LISREL was improved, thereby giving birth to LISREL VI (Jöreskog and Sörbom 1986), which offered a more diverse range of estimation methods. Another method traditionally used for performing structural equation analysis was EQS (abbreviation for "equations") (Bentler 1985). Nowadays, various estimation programs, such as the Analysis of Moment Structures (AMOS) software can facilitate the task

(Arbuckle 1997). The influence of estimation programs on SEM has been so strong, that structural equation models are often referred to as LISREL models, yet international literature reports them as structural equation models or SEMs.

One of the goals of empirical research is to discover causal relationships between variables. This goal is achievable when researchers work with experimental and controllable concepts, such as physical phenomena. However, most of the variables studied in social science and behavioral studies are impossible to control, which is why researchers must rely on other alternatives. The social sciences frequently study abstract and intangible concepts known as constructs, which can only be measured indirectly with the help of indicators. In this sense, SEMs are useful tools in the study of linear causal relationships. These models do not prove causality but can support researchers in decision-making situations by rejecting those hypotheses that contradict the data or the structure of the covariance (i.e., the subjacent relationships between the variables) (Casas 2002).

Overall, a structural equation model comprises two models: the measurement model and the structural model. A measurement model represents the part that can be measured; that is, the part that describes how latent variables are measured by their corresponding manifest indicators. Measurement models inform on the validity and reliability of the observed indicators. On the other hand, a structural model describes the relationships between latent variables. The importance of a SEM-based analysis resides in the ability of the analysis to confirm a theory, or explain it to some extent, and build constructs to estimate latent variables with respect to measured variables. SEM-based models are useful tools in disciplines such as psychology, marketing, social sciences, and recently, engineering.

In the industrial engineering domain, the application of SEM is still at its early stages and thus provides great opportunities for improvement. Common SEM-based studies conducted in this area evaluate the impact of information networks on supply chain (SC) performance or assess the effects of SC risk on manufacturing and distribution processes (Swafford et al. 2006). Likewise, the literature reports SEM-based analyses of lean processes and supply logistics integration (Prajogo et al. 2016), SC collaboration (Ramanathan and Gunasekaran 2014), SC flexibility and its impact on knowledge transfer (Blome et al. 2014; Jin et al. 2014), or even the effects of SC flexibility and agility in the fashion industry (Chan et al. 2017). There are also studies aiming at analyzing the relationship between competitiveness and customer satisfaction (Subramanian et al. 2014), as well as the impact of green SC (Mangla et al. 2014), resilience (Govindan et al. 2015) and information systems (Qrunfleh and Tarafdar 2014; Tarafdar and Qrunfleh 2017).

8.3 Structural Equation Modeling (SEM)

Model design and development procedures and methodologies have greatly varied in the last twenty years. Initially, researchers used to work merely with observed variables, and all the underlying structures were clear and evident. The idea of measuring unobserved constructs emerged among the social sciences and fueled the evolution of overall measurement systems, methods, and techniques. Covariance structure models first became popular thanks to Jöreskog, Keesing, and Wiley and their works on simultaneous equations. Later on, from 1967 to 1978, these models were increasingly popularized thanks to the LISREL software and related programs.

Covariance structure models are within interdependence models for a confirmatory factor analysis of any order or degree and for dependency models in the case of a causal analysis. Scales can be either measurable or non-measurable (categorical scales vs. ordinal scales), and they indicate the level of dependence at various levels. The use of causal models has exponentially increased over time, since they allow researchers to analyze complex construct networks, wherein each network is measured by multiple variables (Lévy-Mangin and Varela 2006). In this sense, causal models can be considered as superior if compared to traditional statistical techniques, since they can incorporate abstract and unobservable constructs (Fornell 1982, 1983).

SEM is a second-generation statistical analysis technique employed to develop or test research theories. SEM includes a family of multivariate statistical tools to estimate effects and relationships among multiple variables. SEM's major advantage is that it proposes the type and direction of the hypothetical relationships between variables. Then, it estimates the parameters (Ruiz et al. 2010). Finally, note that structural equations are not only used for covariance structures, but also for variance structures in which a given percentage of variance can be explained through explanatory constructs and variables. Therefore, it is important to mention that modeling is possible thanks to the application of Partial Least Squares (PLS), which estimate the parameters. This type of modeling is known as PLS-SEM.

8.3.1 *Partial Least Squares (PLS)*

PLS-based SEM allows researchers to perform multiple regressions between latent variables (Batista and Coenders 2000). The goal is to depict in a model how some variables affect other variables, considering they are interrelated (Valencia et al. 2017). PLS is a multivariate analysis technique for testing structural equation models. It allows researchers to develop a comprehensive model in order to estimate path models that involve latent constructs indirectly measured by multiple indicators. Similarly, PLS can reflect the theoretical–empirical conditions where some theoretical situations are scarce or changing (Wold 1985).

The goal of PLS-based modeling is to predict which latent and observed variables are dependent. This can be achieved by maximizing the explained variance (R^2) contained in dependent variables. Definitely, PLS is designed to explain the variance of dependent latent variables, that is, to analyze the importance of the relationships and the resulting R^2 coefficient. Likewise, if compared with covariance-based methods, the PLS-based technique is rather confirmatory, not exploratory. Rather than estimating the variance of all the variables, PLS analyzes the data and relies on a sequence of Ordinary Least Squares (OLS) iterations and multiple regressions performed for each construct.

As a SEM technique, PLS sees each construct as a theoretical construct represented by its own indictors. However, the relationships between constructs must be defined with respect to previously established knowledge (theory) about the research phenomenon (Loehlin 1998). PLS relies on an iterative algorithm in which parameters are calculated by a series of least squares regression. The term partial refers to the fact that the iterative procedure involves separating the parameters instead of estimating them simultaneously (Batista and Coenders 2000). Furthermore, PLS can deal with complex models that contain a large number of constructs and interrelationships. It offers less strict suppositions on data distribution and can work with nominal, ordinal, or even interval data.

Researchers have demonstrated that PLS-based mathematical methods are fairly rigorous and robust (Romero et al. 2006). That said, the mathematical model is flexible in the sense that it does not establish premises related to measurement levels, data distribution, or sample sizes. The main goal is to perform a predictive causal analysis on complex problems that are backed up by little theory or research. It is a correlation-based technique designed to extract the main components from an *X* matrix of predictor variables and those from the related *Y* matrix to better predict the variables of the *Y* matrix. The main components of the *X* matrix are selected in a way they can completely predict the variables of the *Y* matrix. Therefore, the components of both matrices are intimately interrelated.

In conclusion, PLS can be a powerful tool thanks to its flexibility: It demands the least number of requirements in terms of measurement scales, sample size, and residual distributions. In large-sample models, the findings from both approaches (PLS-based and covariance-based) are different (Loehlin 1998). Sample size has an impact on the robustness of the statistics. As Gefen et al. (2000) suggest, even in PLS, the sample size should be a large multiple of the number of constructs in the model, since PLS is based on linear regression. Experts recommend using at least ten times more data points than the number of items in the most complex construct in the model (Barclay et al. 1995).

PLS algorithms were originally developed by Wold (1985) to address problems in the estimation procedures when multicollinearity and overparameterization occur (Chin 1998). Likewise, PLS can model both formative and reflective constructs. The former are those indicators that form or determine a construct, whereas the latter are a reflection of the underlying variation in the construct (Diamantopoulos 2008; Bollen 1989). As a result of its ability to model latent constructs under non-normality conditions and with small-sized and medium-sized samples (Chin et al. 2003), the PLS optimization technique has recently become an exclusive object of study.

8.3.2 Characteristics of PLS Path Modeling

PLS path modeling has the following four characteristics: (1) normality in data distribution is not assumed, since it is a nonparametric method that can work with relatively non-normal data; (2) few variables can be used for each construct; (3) the model can include a large number of indicator variables (more than 50 attributes); and (4) it is assumed that all the measured variance is used to explain or predict the proposed causal relationships (Hair et al. 2012, 2013). PLS-SEM methods are nonparametric optimization techniques that do not need the usual requirements of normal data to apply the maximum likelihood estimation (MLE) method. PLS-SEM methods represent analytic techniques associated with regression, since they combine a prediction-oriented econometric perspective with a psychometric viewpoint. This characteristic allows developing models with latent variables and their corresponding indicators. Similarly, it allows for greater flexibility when modeling a theory (Roldán and Cepeda 2013). Table 8.3 introduced below reports the foremost advantages of PLS path modeling.

PLS suits better predictive applications and theory development. It can be employed to suggest possible relationships and propositions that can be eventually proved, or even to confirm research theories (Chin 2010). Furthermore, PLS path modeling does not impose any assumption whatsoever regarding a specific distribution of data, and it avoids two serious problems: inappropriate solutions and factors indeterminacy. Finally, PLS path modeling sets minimum requirements as regards measurement scales (ordinal or nominal); that is, it does not demand scale uniformity (Sosik et al. 2009).

PLS modeling is robust against three inadequacies (a) skewed instead of symmetric distributions for manifest variables, (b) multicollinearity within blocks of manifest variables and between latent variables, and (c) misspecification of the structural model with small samples (Reinartz et al. 2009; Ringle et al. 2009a; Chin 2010). This method might be more appropriate when the objective is application or prediction, when the research phenomenon is relatively new or changing, when the

Table 8.3 Characteristics of PLS path modeling

Criterion	PLS characteristic
Approach	Variance-based
Objective	Prediction-oriented
Assumptions	Nonparametric (predictor specification)
Hypothesis	Optimal prediction precision
Latent variable scores	Explicitly estimated
Parameter estimates	Consistent as indicators and sample size increase
Minimal sample size	30–100 cases
Epistemic relationship	Can be modeled in either formative or reflective mode
Implications	Optimal for prediction accuracy

research work is interactive, or when the model is complex and has multiple indicators or latent variables, regardless of the level of solidness of the theoretical context (Chin 2010).

PLS path modeling can explain causal relationships between multiple variables, each one of them measured through one or more indicators. Unobservable variables hold a given relationship with observed variables. Such relationship can be viewed as a reflection effect. Each indicator can be defined as a linear function of the latent variable plus an error term. The correlation among indicators increases internal consistency. This is usually confirmed by the dimensionality, reliability, and validity tests performed on the model. Similarly, another way to view variables is as a relationship of a formative effect, in which latent variables are not always represented in the traditional fashion. They are rather composed by causal indicators, which are the linear combination of those indicators plus a disturbance.

8.3.3 Observed Variables and Latent Variables

One of the most relevant concepts in SEM is that of latent variable. Latent variables cannot be directly observed or measured with a generally accepted instrument (Schumacker and Lomax 2004). Similarly, latent variables are composed of manifest variables, also known as observed variables or indicators. In PLS path modeling, a latent variable is obtained through a linear combination of its observed variables (indicators) (Loehlin and Beaujean 2016). It is generally assumed that no measurement is perfect (Bollen 1989). As reported by Haenlein and Kaplan (2004), every real-world observation comes with a measurement error, which can comprise two parts: a random error and a systematic error. Random errors are statistical fluctuations mainly caused by the order of the survey items or by biased responses. On the other hand, systematic errors are due to the method's variance. In this sense, the value of an item is always the sum of three parts: the real value, the random error value, and the systematic error value.

When relying on PLS path modeling, three steps must be followed: Determine the nature of the relationship between indicators and constructs, assess indicator reliability and validity, and interpret structural coefficients and thus determine the model's adequacy. Additionally, PLS path models are analyzed and interpreted in two stages (Roldán and Cepeda 2013):

– Stage 1: Assess model reliability and validity. The goal at this stage is to determine whether the theoretical concepts under study are being appropriately measured through the observed variables. Reflective constructs are used to measure validity (i.e., the used measurement exactly measures what it is supposed to measure) and reliability (i.e., consistency of the results), whereas formative constructs are used to measure multicollinearity in indicators and the weights of manifest variables.

– Stage 2: Assess the structural model. The goal at this stage is to assess the magnitude and significance of the model relationships. This stage considers aspects such as explained variance, standardized regression coefficients, as well as their respective significance levels, to name but a few.

These two stages are performed to guarantee construct validity and reliability before the researcher can draw conclusions from the model (Barclay et al. 1995). These two stages are thoroughly discussed in the following chapter.

8.3.4 Sample Size in PLS Path Modeling

The PLS method usually guarantees high statistical prediction accuracy, even with small-sample models (e.g., 35–50 cases). However, when large samples are involved (i.e., more than 200 cases), estimation precision accuracy usually increases (Hair et al. 2009). Moreover, covariance-based and variance-based PLS methods usually differ in accuracy with large-sized samples.

8.3.5 Specifications of PLS Path Modeling

SEM is a unique, systematic, and integrative analysis technique because it can evaluate both measurement models and structural models. Measurement models show how each latent variable is represented by indicator variables, whereas structural models describe hypothesized causal relationships that occur among a set of dependent and independent constructs. Measurement and structural models can be mathematically represented by using simultaneous equations. Since structural equation models are developed according to available literature, hypothesized causal relationships can be visually represented. Structural equation models can model the degree to which observed variables do not perfectly describe a construct of interest.

Similarly, they can incorporate unobservable constructs measured through indicators (i.e., items, attributes, observed variables) and model the relationships among multiple predictor variables (i.e., independent or exogenous variables) and result variables (i.e., dependent or endogenous variables). Finally, structural equation models can combine and compare a priori knowledge and hypotheses with empirical data. To represent measurement and structural models, there must be enough indicators of each latent variable. A rule of thumb is that there need to be at least two indicators per latent variable in order to avoid problems when calculating degrees of freedom. That said, the ideal number of indicators is five or six (Hair et al. 2009). Figure 8.4 illustrates an example of both a measurement model and a structural model.

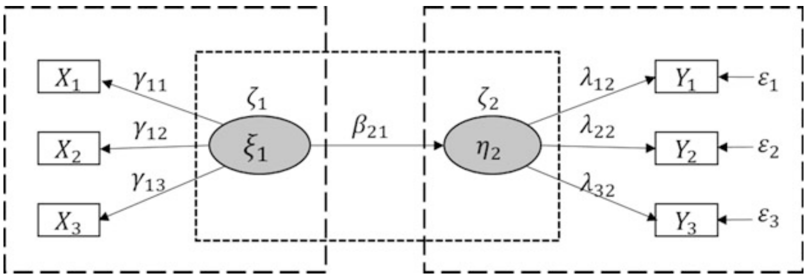

Fig. 8.4 A measurement model and a structural model in SEM. *Source* Own

8.3.6 Basic Terminology

This section discusses basic SEM terminology for both measurement models and structural models. The figures introduced below support the presented terminology. Each one of these figures is a part of Fig. 8.4, which was presented in the previous section.

To begin with, it is important to bear in mind that those variables that cannot be directly measured, but are rather represented by one or more observed variables, are known as constructs. Graphically, constructs are represented by circles or ellipses. There are two types of constructs: exogenous (ξ) and endogenous (η). Exogenous constructs act as predictor or causal variables, whereas endogenous constructs receive the causality of exogenous constructs. Indicators (or manifest variables) are observed variables representing attributes or items obtained from questionnaires or surveys. Graphically, observed variables are represented by squares (Roldán and Cepeda 2013).

Figure 8.5 illustrates a set of unidirectional relationships between variables. These relationships are depicted by arrows and represent those causal relationships than can occur internally (i.e., between constructs) and externally (i.e., between each latent variable and its indicators). Reflective indicators are unobservable constructs that reflect preexisting theoretical constructs. On the other hand, formative constructs cause or give rise to latent theoretical constructs.

Figure 8.6 depicts a series of parameters to be estimated. The direction of the arrows indicates the direction of the causality. As the figure illustrates, causality goes from construct (η) to its indicators (Y_i), and these indicators must be highly correlated. In other words, they must have high internal consistency levels (as defined by Cronbach's alpha, the composite reliability index, and the average variance extracted) to be able to explain that construct. The error is associated with the individual measures of each indicator.

The reflective measure for the *i*th indicator is (Y_i); (η) represents the construct, and (λ_i) is the factor loading of construct η over Y_i. Similarly, ε_i is the specific measurement error of Y_i, and n stands for the number of reflective indicators used to value the construct. This is denoted in Eq. 8.5.

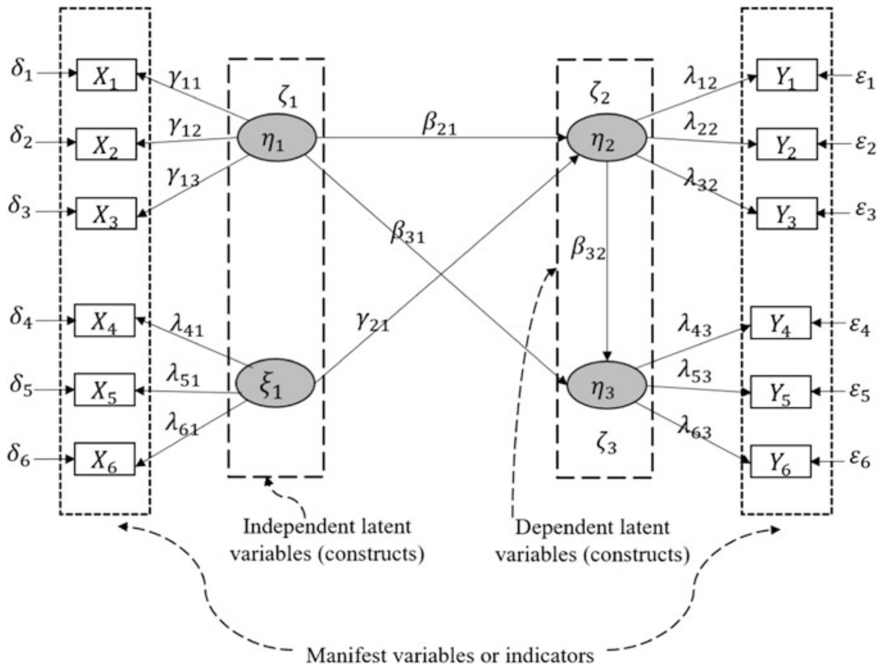

Fig. 8.5 Structural equation model with indicators, example. *Source* Own

$$Y_i = \lambda_i \eta + \varepsilon_i, i = 1, \ldots, n \tag{8.5}$$

Figure 8.6 also depicts the regression coefficients between endogenous latent variables β_{ij} and exogenous latent variable γ_{ji}, as well as the equation errors in structural model ζ_1. Causality arrows emerge from exogenous latent variables and are directed toward endogenous latent variables. Measurement errors for exogenous latent variables are noted as δ_i.

8.3.6.1 Estimations in PLS Path Modeling

Making estimations in the structural model implies estimating all the parameters. In covariance-based SEM, parameters are usually estimated using the maximum likelihood estimation (MLE) method. The goal of MLE is to find the parameter values that maximize the likelihood function, given the observations (Lomax and Schumacker 2012). Ordinary Least Squares are another common estimation method. OLS is a PLS-based and iteration-based method that can estimate unknown parameters through simple and multiple regressions (Chin and Newsted 1999). Thanks to a bootstrapping or resampling procedure, the OLS method diminishes convergence effects and finds, after a few iterations, an optimal solution.

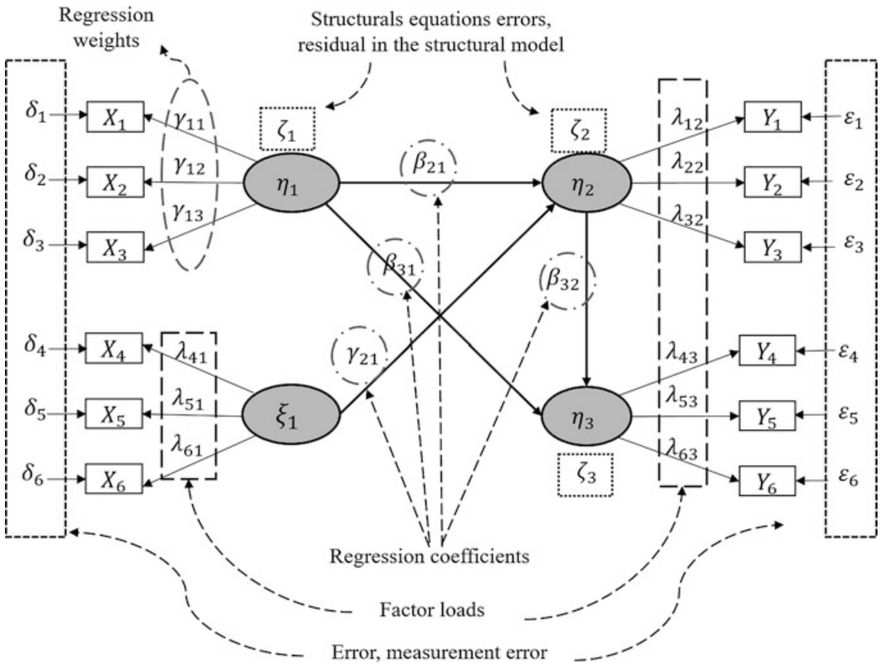

Fig. 8.6 Parameters to be estimated in a structural equation model. *Source* Own

Considering Fig. 8.7 as the reference, the estimation process can be explained as follows:

- The first iteration shows an initial value for η by simply adding values $Y_1 \ldots, Y_j$ (i.e., factor loadings $\lambda_1 \ldots, \lambda_j$ are set to 1).
- To estimate weights $\gamma_1 \ldots, \gamma_i$ in the regression analysis, η is the dependent variable and $X_1, \ldots X_i$ are the independent variables.
- These estimations are used as weightings in a linear combination of $X_1, \ldots X_i$, thereby giving a value for ξ.

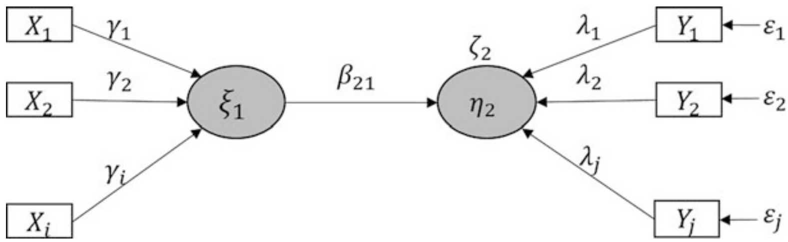

Fig. 8.7 Parameter estimation process diagram. *Source* Own

- Factor loadings $\lambda_1 \ldots, \lambda_j$ are estimated through simple regressions of $\gamma_1 \ldots, \gamma_i$ over ξ. The previous loadings are transformed into weightings to establish a linear combination of $\gamma_1 \ldots, \gamma_i$ as the new estimation for η.
- The procedure is repeated until the difference between the subsequent iterations is small.
- Finally, the simple regression coefficient β is calculated as the difference between the punctuations of both latent variables: ξ and η.
- This segmentation process for the estimation of parameters is useful for complex models and small samples.

8.3.7 Evaluation Criteria for the Measurement Model

The measurement model is employed to assess the reliability of the items contained in a construct or latent variable. The most common latent variable coefficients are those of internal reliability, composite reliability, convergent validity, and discriminant validity. However, it is also imperative to consider aspects such as multicollinearity, which is usually measured by the Variance Inflation Factors (VIF) index. The following paragraphs thoroughly discuss each one of these latent variable coefficients.

8.3.7.1 Reliability and Internal Consistency

Item reliability is measured using the loadings associated to a construct, which must be higher than 0.70. This implies that the variance shared between the construct and its indicators is higher than the error variance. Loadings of values 0.50 and 0.60 can be accepted at early stages of scale development (Chin 1998). Internal consistency is a measure of how well a series of items explain a construct, whereas composite reliability involves the standardized loading for each item and the measurement error. Equation 8.6 introduces the reliability estimation formula.

$$\rho_n = \frac{\left(\sum \lambda_i\right)^2}{\left(\sum \lambda_i\right)^2 + \sum \varepsilon_i} \tag{8.6}$$

where ρ_n stands for construct reliability; λ_i represents the standardized loadings of each observed variable; and ε_i indicates the variance error for each observed variable (Fornell and Larcker 1981).

8.3.7.2 Convergent Validity

Convergent validity implies that a given number of items represent the unidimensionality of a construct (Ringle et al. 2009b). Unidimensionality is measured through the average variance extracted index (AVE), which measures the overall amount of variance in the indicators accounted for by the latent construct. A rule of thumb is to set 0.5 as the minimum acceptable value, which implies that over 50% of the variance of a construct is due to its indicators.

8.3.7.3 Discriminant Validity

Discriminant validity measures to what extent a construct shares more variance with its indicators than with other model constructs. Discriminant validity can be confirmed by demonstrating that the correlations between the constructs are lower than the square root of the AVE. Another way to confirm discriminant validity is to analyze the correlations between the scores of a targeted construct and the scores of the items from the other non-targeted constructs (i.e., cross-loadings). Cross-loadings indicate how strongly a construct item loads on the other non-targeted factors. Constructs must load stronger on their corresponding items than on any other item from any other model construct.

8.3.7.4 Multicollinearity

Multicollinearity refers to a high degree of correlation (linear dependency) among several independent variables or indicators. Collinearity in constructs is usually measured with the VIF index, setting 3.3 as the maximum value (Hair et al. 2012). Finally, to assess measurement models, statistical significance is considered by using a two-tailed Student's t-distribution. A level of significance equal to or higher than 0.5 indicates that a targeted indicator is relevant to a construct.

8.3.7.5 Evaluation Criteria for the Structural Model

To evaluate the fit of a structural model, the research hypotheses must be validated through a significance test performed on each of the estimated coefficients. The one-tailed t-test is performed in situations where researchers predict a relationship or difference in a specific direction (i.e., positive or negative relationships) (Hair et al. 1999); however, when researchers can predict a relationship or difference but do not know in what direction, a two-tailed t-test is performed. A model's fit is measured according to the level of prediction for the independent latent variables, as indicated by R-Squared (R^2). R^2 values indicate the overall amount of variance in dependent latent variables that can be explained by the model. Every path or relationship between constructs should have an R^2 value higher than 0.3. Moreover, predictive variance for each dependent construct, as indicated by Q^2, must be higher than 0. All the latent variable coefficients (for measurement models) and model fit and quality indices (for structural models) are thoroughly discussed in the following chapter, which addresses the methodology of this work.

References

Akkermans HA, Bogerd P, Yücesan E, van Wassenhove LN (2003) The impact of ERP on supply chain management: exploratory findings from a European Delphi study. Eur J Oper Res 146(2): 284–301. https://doi.org/10.1016/S0377-2217(02)00550-7

Arbuckle J (1997) Amos users' guide, version 3.6. Marketing Division, SPSS Incorporated.

Autry CW, Grawe SJ, Daugherty PJ, Richey RG (2010) The effects of technological turbulence and breadth on supply chain technology acceptance and adoption. J Oper Manag 28(6):522–536. https://doi.org/10.1016/j.jom.2010.03.001

Avelar-Sosa L, García-Alcaraz JL, Cedillo-Campos MG (2014) Techniques and attributes used in the supply chain performance measurement: tendencies. In: García-Alcaraz JL, Maldonado-Macías AA, Cortes-Robles G (eds) Lean manufacturing in the developing world: methodology, case studies and trends from Latin America. Springer, Cham, pp 517–541. https://doi.org/10.1007/978-3-319-04951-9_25

Barclay D, Higgins C, Thompson R (1995) The partial least squares (pls) approach to casual modeling: personal computer adoption ans use as an illustration

Batista JM, Coenders G (2000) Modelos de ecuaciones estructurales: modelos para el análisis de relaciones causales.

Bentler PM (1985) Theory and implementation of EQS: a structural equations program. BMDP Statistical Software

Blalock H (1964) Causal inferences in nonexperimental research, University of North Carolina Press. citeulike-article-id:106824.

Blome C, Paulraj A, Schuetz K (2014) Supply chain collaboration and sustainability: a profile deviation analysis. Int J Oper Prod Manag 34(5):639–663. https://doi.org/10.1108/IJOPM-11-2012-0515

Bollen KA (1989) A new incremental fit index for general structural equation models. Sociol Methods Res 17(3):303–316. https://doi.org/10.1177/0049124189017003004

Boudon R (1965) A method of linear causal analysis: dependence analysis. Am Sociol Rev 30(3): 365–374. https://doi.org/10.2307/2090717

Casas M (2002) Los modelos de ecuaciones estructurales y su aplicación en el Índice Europeo de Satisfacción del Cliente. In X Jornadas Madrid 2002-ASEPUMA. Madrid, España, pp 1–11

Chan ATL, Ngai EWT, Moon KKL (2017) The effects of strategic and manufacturing flexibilities and supply chain agility on firm performance in the fashion industry. Eur J Oper Res 259(2): 486–499. https://doi.org/10.1016/j.ejor.2016.11.006

Chin WW (1998) The partial least squares approach to structural equation modeling. Modern Methods bus Res 295(2):295–336

Chin WW (2010) How to write up and report PLS analyses. Handbook of partial least squares, pp 655–690

Chin WW, Marcolin BL, Newsted PR (2003) A partial least squares latent variable modeling approach for measuring interaction effects: results from a monte carlo simulation study and an electronic-mail emotion/adoption study. Inf Syst Res 14(2):189–217. https://doi.org/10.1287/isre.14.2.189.16018

Chin WW, Newsted PR (1999) Structural equation modeling analysis with small samples using partial least squares. Statistical strategies for small sample research, 1(1):307–341

Diamantopoulos A (2008) Formative indicators: introduction to the special issue. J Bus Res 61(12):1201–1202
Duncan OD (1966) Path analysis: sociological examples. Am J Sociol 72(1):1–16. https://doi.org/10.1086/224256
Fornell C (1982) A second generation of multivariate analysis. 2. Measurement and evaluation, vol 2. Praeger
Fornell C (1983) Issues in the application of covariance structure analysis: a comment. J Consum Res 9(4):443–448
Fornell C, Larcker DF (1981) Evaluating structural equation models with unobservable variables and measurement error. J Market Res 18(1):39–50. https://doi.org/10.2307/3151312
García Ochoa JJ, León Lara JdD, Nuño de la Parra JP (2017) Propuesta de un modelo de medición de la competitividad mediante análisis factorial. Contaduría y Administración 62(3):775–791. https://doi.org/10.1016/j.cya.2017.04.003
Gefen D, Straub D, Boudreau M-C (2000) Structural equation modeling and regression: guidelines for research practice. Commun Assoc Inf Syst 4(1):7
Govindan K, Azevedo SG, Carvalho H, Cruz-Machado V (2015) Lean, green and resilient practices influence on supply chain performance: interpretive structural modeling approach. Int J Environ Sci Technol 12(1):15–34. https://doi.org/10.1007/s13762-013-0409-7
Haenlein M, Kaplan AM (2004) A beginner's guide to partial least squares analysis. Underst Stat 3(4):283–297. https://doi.org/10.1207/s15328031us0304_4
Hair JF, Anderson RE, Hair JF, Tatham R (2009) Análisis multivariante, texto en línea, consultado el 4
Hair JF, Anderson RE, Tatham RL, Black WC (1999) Análisis multivariante, vol 491. Prentice Hall Madrid
Hair JF, Ringle CM, Sarstedt M (2013) Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance.
Hair JF, Sarstedt M, Ringle CM, Mena JA (2012) An assessment of the use of partial least squares structural equation modeling in marketing research. J Acad Market Sci 40(3):414–433. https://doi.org/10.1007/s11747-011-0261-6
Jin Y, Vonderembse M, Ragu-Nathan TS, Smith JT (2014) Exploring relationships among IT-enabled sharing capability, supply chain flexibility, and competitive performance. International Journal of Production Economics 153 (Supplement C):24–34. https://doi.org/10.1016/j.ijpe.2014.03.016
Jöreskog KG (1988) Analysis of covariance structures. In: Nesselroade JR, Cattell RB (eds) Handbook of multivariate experimental psychology. Springer US, Boston, MA, pp 207–230. https://doi.org/10.1007/978-1-4613-0893-5_5
Jöreskog KG, Sörbom D (1986) LISREL VI: analysis of linear structural relationships by maximum likelihood, instrumental variables, and least squares methods. Scientific Software
Jöreskog KG, van Thillo M (1973) Lisrel: a general computer program for estimating a linear structural equation system.
Kim D, Cavusgil ST, Cavusgil E (2013) Does IT alignment between supply chain partners enhance customer value creation? An empirical investigation. Indust Market Manag 42(6): 880–889. https://doi.org/10.1016/j.indmarman.2013.05.021
Kline RB (2005) Methodology in the social sciences. Principles and practice of structural equation modeling. Guilford Press, New York
Lévy-Mangin JP, Varela J (2006) Modelización con estructuras de covarianzas en ciencias sociales. Temas esenciales, avanzados y aportaciones especiales. A Coruña, Netbiblo
Lévy J-P, Varela J (2003) Análisis multivariable para las ciencias sociales. Editorial Pearson Educación, Madrid
Loehlin JC (1998) Latent variable models: an introduction to factor, path, and structural analysis. Lawrence Erlbaum Associates Publishers
Loehlin JC, Beaujean AA (2016) Latent variable models: an introduction to factor, path, and structural equation analysis. Taylor & Francis

Lomax RG, Schumacker RE (2012) A beginner's guide to structural equation modeling. Routledge Academic New York, NY
Lu C-S, K-h Lai, Cheng TCE (2007) Application of structural equation modeling to evaluate the intention of shippers to use Internet services in liner shipping. Eur J Oper Res 180(2):845–867. https://doi.org/10.1016/j.ejor.2006.05.001
Lu X-H, Huang L-H, Heng MSH (2006) Critical success factors of inter-organizational information systems—a case study of Cisco and Xiao Tong in China. Inf Manag 43(3):395–408. https://doi.org/10.1016/j.im.2005.06.007
Mangla S, Madaan J, Sarma PRS, Gupta MP (2014) Multi-objective decision modelling using interpretive structural modelling for green supply chains. Int J Logistics Syst Manag 17(2): 125–142
Montgomery DC, Peck EA, Vining G (2006) Introducción al análisis de regresión lineal.
Pérez E, Medrano LA, Sánchez Rosas J (2013) El path analysis: conceptos básicos y ejemplos de aplicación. Revista Argentina de Ciencias del Comportamiento 5(1):52–66
Prajogo D, Oke A, Olhager J (2016) Supply chain processes: linking supply logistics integration, supply performance, lean processes and competitive performance. Int J Oper Prod Manag 36(2):220–238. https://doi.org/10.1108/IJOPM-03-2014-0129
Qrunfleh S, Tarafdar M (2014) Supply chain information systems strategy: impacts on supply chain performance and firm performance. International Journal of Production Economics 147 (Part B):340–350. https://doi.org/10.1016/j.ijpe.2012.09.018
Ramanathan U, Gunasekaran A (2014) Supply chain collaboration: impact of success in long-term partnerships. International Journal of Production Economics 147 (Part B):252–259. https://doi.org/10.1016/j.ijpe.2012.06.002
Ranganathan C, Teo TSH, Dhaliwal J (2011) Web-enabled supply chain management: Key antecedents and performance impacts. Int J Inf Manag 31(6):533–545. https://doi.org/10.1016/j.ijinfomgt.2011.02.004
Reinartz W, Haenlein M, Henseler J (2009) An empirical comparison of the efficacy of covariance-based and variance-based SEM. Int J Res Market 26(4):332–344. https://doi.org/10.1016/j.ijresmar.2009.08.001
Ringle CM, Götz O, Wetzels M, Wilson B (2009a) On the use of formative measurement specifications in structural equation modeling: A Monte Carlo simulation study to compare covariance-based and partial least squares model estimation methodologies. http://dx.doi.org/10.2139/ssrn.2394054
Ringle CM, Sinkovics RR, Henseler J (2009b) The use of partial least squares path modeling in international marketing. In: New Challenges to International Marketing, vol 20. Advances in International Marketing, vol 20. Emerald Group Publishing Limited, pp 277–319. https://doi.org/10.1108/s1474-7979(2009)0000020014
Roldán JL, Cepeda G (2013) Modelos de Ecuaciones Estructurales basados en la Varianza: Partial Least Squares (PLS) para investigadores en Ciencias Sociales. Universidad de Sevilla, Curso del ICE
Romero SJ, Ponsoda V, Ximénez C (2006) Validación de la estructura cognitiva del test de signos mediante modelos de ecuaciones estructurales. Psicothema 18(4):835–840
Ruiz MA, Pardo A, San Martín R (2010) Modelos de ecuaciones estructurales. Papeles del Psicólogo 31(1):34–45
Schumacker RE, Lomax RG (2004) A beginner's guide to structural equation modeling. Psychology Press
Silva C, Schiattino I (2008) Modelos de ecuaciones estructurales¿ qué es eso? Cienc Trab 10(29):106–110
Sosik J, Kahai S, Piovoso M (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(1):5–36. https://doi.org/10.1177/1059601108329198
Su Y-f, Yang C (2010a) A structural equation model for analyzing the impact of ERP on SCM. Expert Syst Appl 37(1):456–469. https://doi.org/10.1016/j.eswa.2009.05.061

Su Y-f, Yang C (2010b) Why are enterprise resource planning systems indispensable to supply chain management? Eur J Oper Res 203(1):81–94. https://doi.org/10.1016/j.ejor.2009.07.003

Subramanian N, Gunasekaran A, Yu J, Cheng J, Ning K (2014) Customer satisfaction and competitiveness in the Chinese E-retailing: structural equation modeling (SEM) approach to identify the role of quality factors. Expert Syst Appl 41(1):69–80. https://doi.org/10.1016/j.eswa.2013.07.012

Swafford PM, Ghosh S, Murthy N (2006) The antecedents of supply chain agility of a firm: scale development and model testing. J Oper Manag 24(2):170–188. https://doi.org/10.1016/j.jom.2005.05.002

Swafford PM, Ghosh S, Murthy N (2008) Achieving supply chain agility through IT integration and flexibility. Int J Prod Econ 116(2):288–297. https://doi.org/10.1016/j.ijpe.2008.09.002

Tarafdar M, Qrunfleh S (2017) Agile supply chain strategy and supply chain performance: complementary roles of supply chain practices and information systems capability for agility. Int J Prod Res 55(4):925–938. https://doi.org/10.1080/00207543.2016.1203079

Valencia JB, Torres AIZ, Paniagua CFO (2017) Variables e Índices de Competitividad de las Empresas Exportadoras, utilizando el PLS. CIMEXUS 10(2):13–32

Weston R, Gore JPA (2006) A brief guide to structural equation modeling. Couns Psychol 34(5):719–751. https://doi.org/10.1177/0011000006286345

Williams LJ, Vandenberg RJ, Edwards JR (2009) Structural equation modeling in management research: a guide for improved analysis. Acad Manag Annals 3(1):543–604

Wold H (1985) Systems analysis by partial least squares. In Nijkamp P, Leitner H, Wrigley N (eds) Measuring the unmeasurable. Dordrecht, the Netherlands: Martinus Nijhoff, pp 221–252

Wright S (1932) The roles of mutation, inbreeding, crossbreeding, and selection in evolution, vol 1. na,

Wright S (1971) Path coefficients and path regressions: alternative or complementary concepts. Causal models in the social sciences 101–114

Zhang C, Dhaliwal J (2009) An investigation of resource-based and institutional theoretic factors in technology adoption for operations and supply chain management. Int J Prod Econ 120(1):252–269. https://doi.org/10.1016/j.ijpe.2008.07.023