Comparison Study between CB-SEM and PLS-SEM for Sustainable Supply Chain Innovation Model

Ahmed El Maalmi and Laila El Abbadi
Engineering Sciences Laboratory
National School of Applied Sciences, Ibn Tofail University
Kenitra, Morocco
ahmed.elmaalmi@uit.ac.ma, laila.elabbadi@uit.ac.ma

Kaoutar Jenoui
Laboratory Smartilab
Moroccan School of Engineering Sciences, EMSI
Rabat, Morocco
k.jenoui@gmail.com

Abstract
Structural equation modeling (SEM) is becoming the most used method when multiple constructs, relationships, and latent and observed variables are involved, two main statistical analysis techniques of SEM can be applied by researchers: Partial Least Squares Structural Equation Modeling (PLS-SEM), and covariance-based (CB-SEM). This paper is presenting a comparison study between the two methods basing on a case study of the sustainable supply chain innovation model for the Moroccan industrial field during the period of 2020. Section I is dedicated to the conceptual model and the two structural analysis techniques presentation. Section II is explaining the methodology. Section III is consolidating the findings revealed where the CB-SEM technique is performed and consistently compared with PLS-SEM.

Keywords
Industry 4.0 technologies, Sustainable Supply Chain, Innovation, Structural equation model.

1. Introduction
SEM (Structural Equation Modeling) is usually used to explain multiple statistical relationships simultaneously through visualization and model validation (Dash and Paul 2021). It is a powerful and robust multivariate statistical analysis technique that enable researchers to examine the inter-relationships among latent constructs based on theories and their respective observable indicator variables (Mahadzirah et al 2019). Complex models can be discussed simply through this technique. It is an extension of traditional linear modeling techniques, e. g., multiple regression analysis and Analysis of Variance (ANOVA), prerequisites for learning SEM. Briefly, it can be defined as a combination of factor analyses and multiple regression analyses simultaneously (Sarstedt et al., 2017; Hair Jr et al., 2017a; Haenlein and Kaplan, 2004, Dash and Paul, 2021). The covariance between the observed variables is explained by this method with detailed analysis of various covariance statistics, e.g., mean, standard deviation, etc.; Recently, the PLS approach has become quite popular among researchers due to its variance based relationship rather than covariance (AlNuaimi et al., 2021; Mueller & Hancock, 2018; Hair Jr et al., 2017b; Hayes et al., 2017); It is different from the traditional multivariate techniques that address only individual objectives; It also verifies alternate models to find the most appropriate relationship among the latent variables. It usually deals with a large sample (Mueller & Hancock, 2018; Hair Jr et al., 2017b; Hayes et al., 2017; Ullman & Bentler, 2003).

The purpose of this paper is to compare both approaches based on various parameters and to provide a possible solution to the dilemma. The rest of the paper is structured as follows. A subsection to discuss the scope and objective of the paper, which explains the need for this study, the objectives, and the research questions. It also includes the contributions of the study. Section 2 relates important points of SEM history, highlights the various characteristics of SEM, presents important communalities between the two approach CB-SEM and PLS SEM, and lists the limitations of each approach basing literature review. Section 3 details the process of CB-SEM and PLS-

SEM in a stepwise manner. Section 4 explains our strategy for the data collection. Section 5 presents the results we get from the two methods. In section 6, all the empirical results from the two methods are discussed and compared. It provides a general discussion, future directions, and limitations. Finally, section 7 concludes this study.

1.1 Objectives

This study aims to the followings: Describing main points of SEM history, resenting CB-SEM method and mathematical formulation, resenting partial least square method and mathematical formulation, comparing application method basing on literature and presenting similitudes and differences, applying the two method PLS-SEM and CB-SEM to the same model and the same database, comparing results in term of: convergence, validation and confirmation of the measurement model, comparing conclusions and limitations with other studies, proposing a validated model with both of the two methods for sustainable supply chain innovation in the Moroccan context.

2. Literature review

2.1 Key advances in history of SEM

The figure bellow is presenting main events of SEM history:

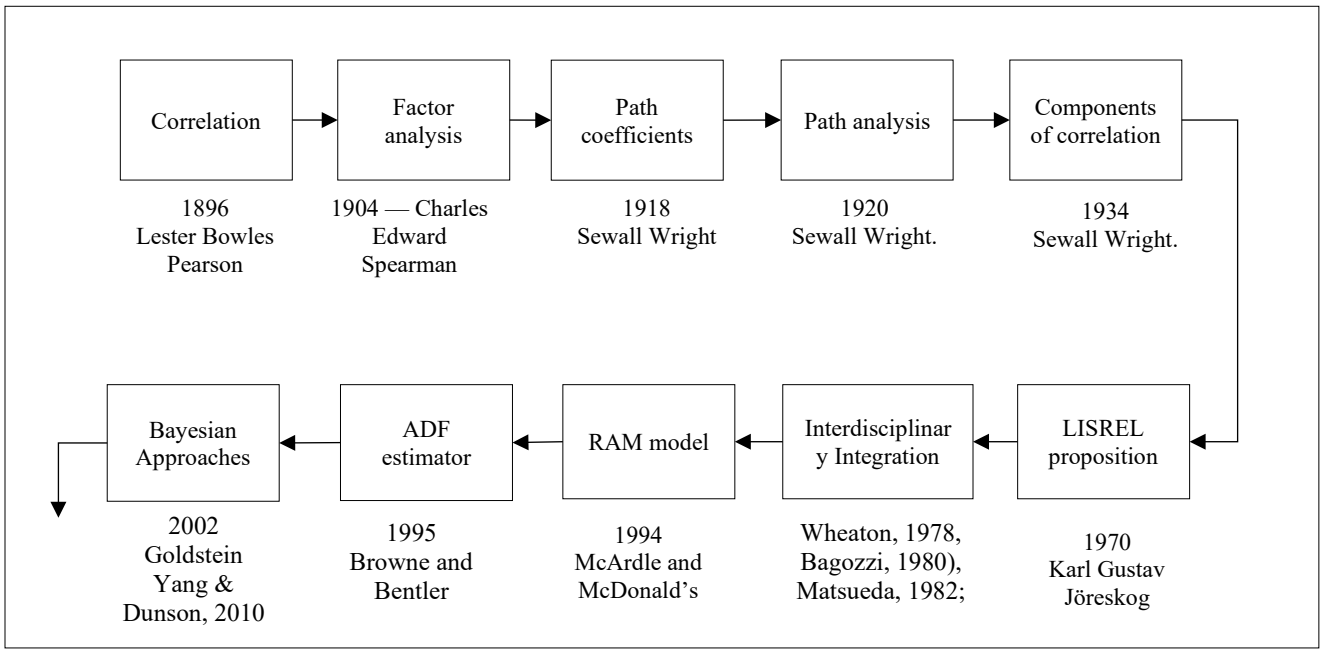

Figure 1. Main events of SEM history

- **Correlation**

Karl Pearson (1896) proposed the correlation coefficient.

$$r_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}\frac{(x_i-\bar{x})(y_i-\bar{y})}{\sigma_x\sigma_y}$$

Pearson (1901a) published a paper on fitting planes by orthogonal least squares, which was the foundation for principal component analysis that was also applied to the analysis of correlation matrices by Hotelling (1933).
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- **Factor analysis**

The early beginnings of SEM development should be reconstructed indirectly on the basis of Spearman's works (1904, 1927), as he laid the foundations for SEM by constructing the first factor model which later became an important measurement part of the more general SEM analytical strategy. Spearman (1904) is often cited in the literature as the founding father of factor analysis. Spearman (1904b) built on Pearson correlations and developed a method of factor analysis.

What Spearman did exactly was to measure general cognitive abilities in humans by using models of the so-called factor analysis

Spearman's work (1904) marked the beginning of the development of factor models which later became the key for the construction of measurement models used in SEM.

- **Path coefficients**

Wright (1918) first proposed the method of path coefficients which was based on partial correlations.
In 1918, Sewall Wright, a young geneticist, published the first application of path analysis, which modeled the bone size of rabbits.

- **Path analysis**

. Path analysis was originally developed by geneticist Sewall Wright in the 1920s to examine the effects of hypothesized models in phylogenetic studies. Wright's analysis involved writing a system of equations based on the correlations among variables influencing the outcome and then solving for the unknown parameters in the model.

. After computing all possible partial correlations of his measures, he was still dissatisfied with the results, which remained far from a causal explanation. Consequently, Wright developed path analysis to impose a causal structure, with structural coefficients on the observed correlations. His substantive application decomposed the variation in the size of an individual bone to various hereditary causes (Hill, 1995). He subsequently applied path analysis to systems of mating, using data on guinea pigs, which laid the basis for much of subsequent population genetics (Hoyle, R. H. (Ed.). (2012). Handbook of structural equation modeling. The Guilford Press.)

The first statement of path analysis comes in this paper: "The correlation between two variables can be shown to equal the sum of the products of the chains of path coefficients along all the paths by which they are connected.". The first path diagrams also were published here
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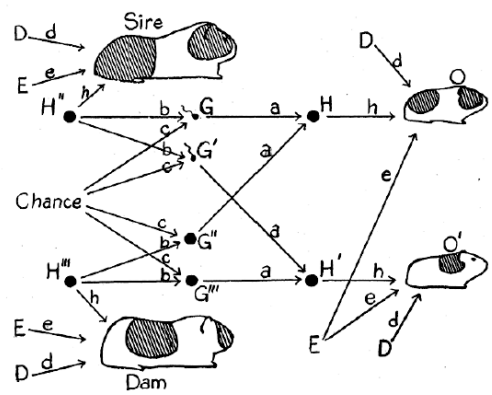

The first published path diagram (Wright, 1920)

Figure 2. Early path diagram

An early path diagram on the importance of heredity and environment in spotted guinea pigs. From Wright (1921b). Copyright granted by the Genetics Society of America. Reprinted by permission.

- **Components of correlation**

Sewell Wright (1934) later developed more general solutions,

It can be shown that the squares of the path coefficients measure the degree of determination by each cause. If the causes are independent of each other; the sum of the squared path coefficients is unity. If the causes are correlated, terms representing joint determination must be recognized. The complete determination of X in figure 6 by factor A and the correlated factors B and C, can be expressed by the equation:

$$a^2 + b^2 + c^2 + 2bcr_{BC} = 1$$

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- **LISREL proposition**

At the first of these meetings (in 1970) Jöreskog presented the basis for LISREL.
In a series of landmark papers, Jöreskog (1970, 1973, 1978) outlined a general approach to covariance analysis and a computer program he called LISREL, which, following econometricians as far back as Frisch and Waugh (1933), stood for "LInear Structural RELations." At about the same time, Keesling (1972) in his Ph.D. dissertation, and Wiley (1973) in the Goldberger-Duncan volume, presented nearly identical models. However, it was Jöreskog's version and software package that came to dominate the field. The LISREL model incorporates factor analysis, simultaneous equation models, and path analysis (as discussed above) into a general covariance structure model (e.g., Jöreskog and Sörbom 2001).

The LISREL model incorporates factor analysis, simultaneous equation models, and path analysis (as discussed earlier) into a general covariance structure model (e.g., Jöreskog & Sörbom, 2001):

- **Interdisciplinaire integration**

The next two decades saw an explosion of the use of structural equation models in many areas of the social sciences, including stratification (e.g., Bielby, Hauser, & Featherman, 1977), social psychology (e.g., Kohn & Schooler, 1982), psychology (e.g., Bentler & Speckart, 1981), marketing (Bagozzi, 1980), mental health (e.g., Wheaton, 1978, 1985), sociology of science (e.g., Hargens, Reskin, & Allison, 1976), criminology (e.g., Matsueda, 1982; Matsueda & Heimer, 1987), adolescence (e.g., Simmons & Blyth, 1987), and population genetics (e.g., Li, 1975).
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- . **RAM Model**

. Karl Jöreskog's Linear Structural Relations model was the foundation for the explosion in SEM

- . **ADF estimator**

Browne's (1984) ADF and elliptical estimators first appeared in Bentler's (1995) EQS program, followed by Jöreskog and Sörbom's (2001) LISREL program. Recent work has examined the finite sample properties of ADF and finds that it works well in very large samples

- **Bayesian Approaches and Latent Class Growth Models**

Bayesian estimation using Markov Chain Monte Carlo (MCMC) algorithms are proving useful for incorporating prior information into confirmatory factor analysis (e.g., Lee, 1981); estimating complex models, such as nonlinear latent variable models (e.g., Arminger & Muthén, 1998); estimating multilevel factor models (Goldstein & Browne, 2002); arriving at a semiparametric estimator (Yang & Dunson, 2010); and drawing inferences about underidentified parameters from the posterior distribution when an informative prior is used (Scheines, Hoijtink, & Boomsma, 1999).

Although the use of factor analysis for modeling panel data on growth was introduced by Tucker (1958) and Rao (1958), it was not until 1990 that Meredith and Tisak (1990) published the treatment within an SEM framework that is still relevant today (see Bollen & Curran, 2006). Meredith and Tisak (1990) showed that individual growth curves, often modeled within a multilevel or mixed model framework (e.g., Raudenbush & Bryk, 2002), can be modeled within a standard SEM

framework by treating the shape of growth curves as latent variables with multiple indicators consisting of the variable at multiple time points. This latent growth curve approach models both covariances and means of observed variables. Figure 2.4 presents a path diagram of a four-wave quadratic latent growth curve model.

SEM has progressed through four general stages: (1) early disciplinary-specific developments of path analysis first from genetics and later sociology, factor analysis from psychology, and simultaneous equation models in economics; (2) cross-disciplinary fertilization between economics, sociology, and psychology, leading to an explosion of empirical applications of SEM; (3) a period of developing methods for handling discrete, ordinal, and limited dependent variables; and (4) a recent period of incorporating statistical advances into the SEM framework, including generalized linear models, mixed effects models, mixture regression models, Bayesian methods, graphical models, and methods for identifying causal effects. The recent period is substantially integrating SEM with the broader statistical literature, which—as the chapters of this volume demonstrate— is making SEM an even more exciting and vibrant tool for the social sciences.

2.2 CB-SEM and PLS SEM

Main recent study in the concern of CB-SEM and PLS SEM comparison:

Table 1. The concern of CB-SEM and PLS SEM comparison

Authors	**Study**	**Results and conclusion**	**Study limitation**

Dash and Paul (2021)	CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting	• The item loadings are usually higher in PLS-SEM than CB-SEM. • The structural relationship is closer to CB-SEM if a consistent PLS algorithm is undertaken in PLS-SEM. • The average variance extracted (AVE) and composite reliability (CR) values are higher in the PLS-SEM method, indicating better construct reliability and validity. • CB-SEM is better in providing model fit indices, whereas PLS-SEM fit indices are still evolving. • CB-SEM models are better for factor-based models like ours, whereas composite-based models provide excellent outcomes in PLS-SEM.	• The model considered was a simple one to keep the explanations to the bare minimum. • The sample size could be raised to a minimum of 1000 with diverse respondents to get a better picture. • Demographic and socio-economic factors as control variables are ignored in this study as it was not our objective. • The specified model used in this study was not composite-based. Still, regular PLS was used to assess it, which might not be a good idea. However, the authors continued with it because of enormous literary support for the same. • Only two software packages from each approach were taken; more competing packages could have been included to assess comprehensively.
Afthanorhan, Awang and Aimran (2020)	An extensive comparison of CB-SEM and PLS-SEM for reliability and validity	• Good standardized loading can increase the reliability and validity of construct representation. • CBSEM is particularly yielded valid and unbiased estimation under confirmatory condition (established theory) compared with PLS-SEM.	• No limitation provided in the study.
Mahadzirah et al. (2019)	Comparison Between CB-SEM and PLS-SEM: Testing and Confirming the Maqasid Syariah Quality of Life Measurement Model	• Although both approaches produced similar results, the CB-SEM is more appropriate for validating and confirming the measurement model. • PLS-SEM is more appropriate for prediction and theory development: when the phenomenon being investigated is relatively new and the measurement models are at the exploratory stage. • PLS-SEM allows the use of small sample size. • CB-SEM is more appropriate for assessing model fit and provide critical examination to obtain meaningful solution, particularly for decision making.	• The sample size of the study is just satisfying the criteria of required size. It is suitable to have enough data to avoid any bias results.
Soo-tai, Do-goan and Chan-yong (2020)	A Comparison Analysis among Structural Equation Modeling (AMOS, LISREL and PLS) Using the Same Data.	• The analysis application LISREL and PLS provides the path coefficient, T-value, and R^2, but AMOS does not present the R^2 value. The R^2 means the explanatory power of the construct.	• The purpose of this study was to compare analyze three representative analytical applications using SEM with the same data. Therefore, we

		• AMOS has the disadvantage that it must be described as T-value instead of R^2 value. If not satisfied, another alternative must be chosen. • LISREL has the highest explanatory power of dependent variables than other analytical tools. • The path coefficients and T-values presented by the analysis results showed similar results for all three analysis tools. • Because of using all three analytical tools, we can say that both advantages and disadvantages exist.	have not found any special superiority among the three analysis tools.

Rigdon et al. (2017)	On Comparing Results from CB-SEM and PLS-SEM: Five Perspectives and Five Recommendations.	• Quality data lead to quality inferences and that no statistical method turns bad data into good data. • It is best to consider the entirety of the research process while using any data analysis method. • Five perspectives are given in the study: - CBSEM and Pls-SEM are two Different Estimators. - The two methods are based on different Models. - The measurement errors must be considered, even with the same studied Phenomena. - Imperfect World (sample size, few indicators), - The Long View (Only repeated examinations of a certain phenomenon provide confidence for the prevalence of some effect). Five recommendations are listed: - Focus on the actual phenomenon abject of the study. - Strong focus on building data sets that can credibly lead to insight. - Use of CB-SEM for a factor model estimation, and PLS-SEM and GSCA to estimate a model of composites. - PLS-SEM is more recommended for data examination and evaluation of many different configurations. - More routine exploration of alternative models for explaining the phenomenon under study.	• The paper is providing five perspectives regarding CB-SEM and Pls-SEM to be considered by researchers. It is recommending five guidelines basing the literature review. No use case is given in this study.
Hair et al. (2017)	PLS-SEM or CB-SEM: updated guidelines on which method to use.	• If the theory being investigated is well established, and the measurement is effectively executed, then CB-SEM often works well. • CB-SEM assumes normality of data distributions, which is seldom met in social sciences research • PLS-SEM is non-parametric and not only works well with non-normal distributions, but also has very few restrictions on the use of ordinal and binary scales, when coded properly.	• No limitation provided in the study.

		• Comparison of the R2 output of the two methods indicates that if prediction is the focus of your research, then PLS-SEM is the preferred method because in a direct comparison with CB-SEM the variance explained in the dependent variables is substantially higher. Overall, therefore, the PLS-SEM method is much more appropriate at the theory development stage than is CB-SEM.	
Amaro, Seabra and Abrantes (2015)	Comparing CB-SEM and PLS-SEM Results: An empirical example.	• The both approaches CB-SEM and Pls-SEM produce similar results • PLS-SEM produced higher Reliability and Convergent Validity Measures, while CB-SEM achieved higher path coefficients.	• The model is study is inspired from a previous model explored by Seabra et al.'s (2014) but do not include all constructs and items. Therefore, it would be noteworthy to compare CB-SEM and PLS-SEM with the initial model as a basis. This point will be taken in consideration by the authors in future work.
Kaufmann and Gaeckler (2015)	A structured review of partial least squares in supply chain management research.	• CBSEM is better grounded in statistical theory than PLS and should be the preferred method of choice if all assumptions are met • PLS is an acceptable analytical method and a realistic alternative, if researchers carefully report their reasons for choosing PLS. • Recent methodological advances, such as confirmatory tetrad analysis, importance-performance matrix analysis, and the use of the PLSc estimator, equip researchers with more flexibility and allow for a more nuanced testing of theoretical concepts.	• The paper evaluates a subset of SCM journals. Include articles from other journals may change or confirm the results and conclusions. • The study focusses mainly on the drawbacks of PLS and do not examine the extent to which CBSEM or other methodologies also might be problematic. • This paper emphasizes basic criteria of PLS analysis, but researchers can benefit from a wider range of recent methodological extensions of PLS.
Costa, MacCann and Roberts (2015)	Testing complex models with small sample sizes: A historical overview and empirical demonstration of what Partial Least Squares (PLS) can offer differential psychology	• Under common constraints of research settings, sample size requirements of PLS may be substantially smaller than those of SEM. • PLS is a useful tool for differential psychology research in scenarios where sample size constrains the use of robust SEM. • PLS offers a viable means to explore and text complex models beyond current limits.	• There are aspects and analyses in PLS that are unique from both SEM and regression that not been explored in the present paper but will hopefully be seen in future publications indicating adoption of this interesting and useful technique.

3. Methods

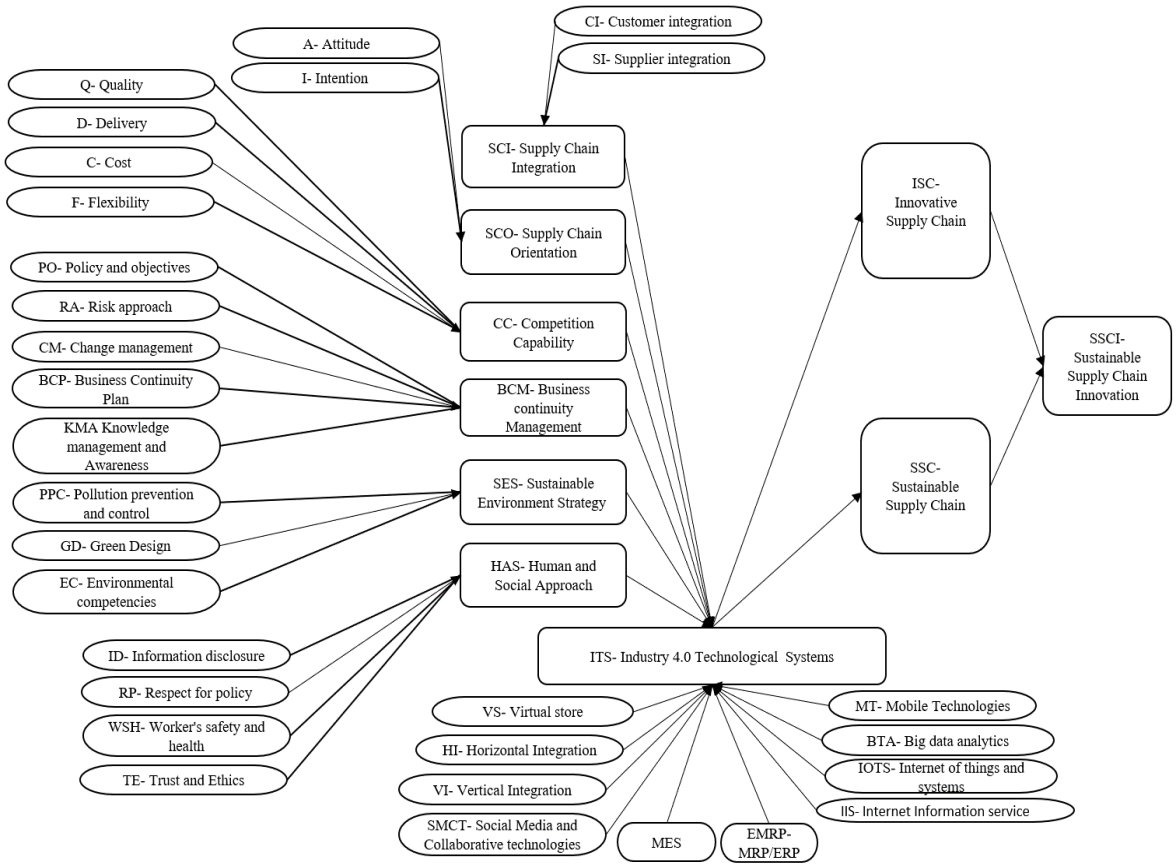

Figure 3. Methods

3.1 Covariance based structural equation modeling

Theoretical basis CB-SEM

. CFA (Confirmatory Factor Analysis) was conducted to validate the constructs and their measurable indicators to confirm the EFA. CFA is conducted to test the EFA results with visualization and model fit. Once CFA is done, the final structural model between the four latent variables was tested with the empirical data. As the authors have discussed earlier, CFA verifies the measurement model, and SEM visualizes the path analysis of relationships among the factors. Once the CFA is conducted successfully, SEM is conducted (See Figure 2:). In a single structural relationship model, two phases are conducted. In the first stage, the items' loadings under the individual constructs are visualized. The relationships between the four factors (as per the conceptual model) are assessed in the second stage.

LISREL Software and application methodology

LISREL, the legendary initial SEM computer program, evolved from rekindled interest in path analysis during the 1960s that resulted from a call for social scientists to reconsider making causal interpretations of nonexperimental data. During the early 1970s the LISREL model was generalized to accommodate confirmatory factor analysis (Jöreskog, 1969), multiple-group analysis (Jöreskog, 1971), and more general models for the analysis of covariance structures (e.g., Jöreskog, 1970)

3.2 Part least squares structural equation modeling

Theoretical basis of PLS-SEM
Smart PLS Software and application methodology
SmartPLS software is a free and user-friendly modeling package for partial least squares analysis. It is supported by a community of scholars centered at the University of Hamburg (Germany), School of Business, under the leadership of Prof. Christian M. Ringle. SmartPLS is a successor to the PLSPath software, which was used in the 1990s. (partial least squares: Regression & Structural Equation Model, 2016 Edition, G. David Garson, Statistical Associates publishing. P35.
Daniel Russo and Klaas-Jan Stol. 2021. PLS-SEM for Software Engineering Research: An Introduction and Survey. ACM Comput. Surv. 54, 4, Article 78 (April 2021), 38 pages. https://doi.org/10.1145/3447580

4. Data Collection

The database used for the comparison study and model validation concerns the Moroccan manufacturing companies including multinational, Moroccan listed, and medium enterprises during 2020. Mainly are explored the sectors of Semiconductors, automotive, aeronautic and mining. The study is performed based on experts' and managers' feedback regarding internal digitalization strategy, innovation strategy, and sustainability in the supply chain. The questionnaire used in online format includes three sections, the first part is the demographic section, which contains information on gender, academic level, role inside the company, and years of experience, the second section contains information related to firms like the number of employees in the firm, activity, annual revenues. The last one is dedicated to questions and items related to the outer model: each factor (or item) is measured based on a Likert scale where the respondent must select an answer according to his agreement: from 1/5 strongly disagree to 5/5 which means strongly agree. Around 300 online questionnaires were emailed, and more than 200 emails were sent on LinkedIn to managerial personnel working in the sampled companies. A total of 239 responses were received, of which 204 were considered accurate for data analysis.

5. Results

5.1 Standardized loading

Table 2. Standardized loading

	PLS-SEM using SmartPLS	CB-SEM using LISREL software		PLS-SEM using SmartPLS	CB-SEM using LISREL software		PLS-SEM using SmartPLS	CB-SEM using LISREL software
A1	0,975	0,936	F2	0,986	0,946	Q1	0,992	0,952
A2	0,974	0,935	GD1	0,975	0,936	Q2	0,992	0,952
BCM1	0,993	0,953	GD2	0,973	0,935	RA1	0,964	0,925
BCM2	0,992	0,953	HI1	0,956	0,917	RA2	0,931	0,894
BCP1	0,927	0,890	HI2	0,728	0,698	RP1	0,988	0,948
BCP2	0,910	0,873	HSA1	0,974	0,935	RP2	0,987	0,947
BDA1	0,988	0,949	HSA2	0,973	0,934	SCI1	0,992	0,952
BDA2	0,988	0,949	I1	0,967	0,928	SCI2	0,992	0,952
C1	0,992	0,952	I2	0,967	0,928	SCO1	0,981	0,941
C2	0,992	0,952	ID1	0,906	0,869	SCO2	0,978	0,939
CC1	0,978	0,939	ID2	0,945	0,907	SES1	0,989	0,950

CC2	0,981	0,941	IOTS1	0,971	0,932	SES2	0,989	0,949
CCS1	0,977	0,938	IOTS2	0,965	0,926	SI1	0,979	0,939
CCS2	0,972	0,933	ISC1	0,980	0,921	SI2	0,981	0,941
CI1	0,980	0,941	ISC2	0,982	0,923	SMCT1	0,993	0,954
CI2	0,980	0,941	ITS1	0,982	0,923	SMCT2	0,993	0,953
CM1	0,808	0,784	ITS2	0,982	0,923	SSC1	0,971	0,932
CM2	0,915	0,887	KM1	0,976	0,917	SSC2	0,971	0,932
D1	0,981	0,951	KM2	0,978	0,919	SSCI1	0,989	0,950
D2	0,981	0,951	MES1	0,954	0,897	SSCI2	0,989	0,949
DS1	0,990	0,960	MES2	0,961	0,904	TE1	0,961	0,923
DS2	0,990	0,960	MT1	0,991	0,932	TE2	0,967	0,928
EC1	0,959	0,931	MT2	0,990	0,931	VI1	0,957	0,918
EC2	0,963	0,934	P1	0,955	0,897	VI2	0,966	0,927
EMRP1	0,981	0,952	P2	0,950	0,893	VS1	0,998	0,958
EMRP2	0,984	0,945	PPC1	0,930	0,874	VS2	0,998	0,958
F1	0,985	0,946	PPC2	0,943	0,886	WSH1	0,928	0,891
						WSH2	0,958	0,920

5.2 Reliability and convergent validity results

Table 3. Reliability and convergent validity results

	PLS-SEM using SmartPLS				CB-SEM using LISREL software			
	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
SSCI	0,995	0,995	0,997	0,995	0,955	0,955	0,957	0,955
SCI	0,991	0,991	0,996	0,991	0,951	0,951	0,956	0,951
SCO	0,941	0,948	0,971	0,944	0,903	0,910	0,932	0,906
CC	0,920	0,934	0,961	0,925	0,883	0,897	0,923	0,888
BCM	0,993	0,994	0,997	0,994	0,953	0,954	0,957	0,954
HAS	0,971	0,971	0,986	0,971	0,932	0,932	0,947	0,932
SES	0,988	0,988	0,994	0,988	0,948	0,948	0,954	0,948
ITS	0,980	0,980	0,990	0,981	0,941	0,941	0,950	0,942
ISC	0,964	0,964	0,982	0,965	0,925	0,925	0,943	0,926
SSC	0,964	0,964	0,982	0,965	0,925	0,925	0,943	0,926
BCP	0,988	0,988	0,994	0,988	0,948	0,948	0,954	0,948
BDA	0,986	0,986	0,993	0,986	0,947	0,947	0,953	0,947
C	0,991	0,991	0,996	0,991	0,951	0,951	0,956	0,951
A	0,972	0,972	0,986	0,973	0,933	0,933	0,947	0,934
CCS	0,763	0,893	0,889	0,800	0,732	0,857	0,853	0,768
CI	0,980	0,980	0,990	0,981	0,941	0,941	0,950	0,942
CM	0,992	0,992	0,996	0,992	0,952	0,952	0,956	0,952
D	0,980	0,980	0,990	0,980	0,941	0,941	0,950	0,941

DS	0,954	0,957	0,977	0,956	0,916	0,919	0,938	0,918
EC	0,892	0,892	0,949	0,902	0,856	0,856	0,911	0,866
EMRP	0,856	0,860	0,933	0,874	0,822	0,826	0,896	0,839
F	0,972	0,972	0,986	0,973	0,933	0,933	0,947	0,934
GD	0,941	0,945	0,971	0,945	0,903	0,907	0,932	0,907
HI	0,903	0,912	0,953	0,911	0,867	0,876	0,915	0,875
I	0,964	0,964	0,982	0,965	0,925	0,925	0,943	0,926
ID	0,352	0,899	0,689	0,563	0,338	0,863	0,661	0,540
IOTS	0,985	0,985	0,992	0,985	0,946	0,946	0,952	0,946
KM	0,989	0,989	0,995	0,989	0,949	0,949	0,955	0,949
MES	0,989	0,989	0,995	0,989	0,949	0,949	0,955	0,949
MT	0,946	0,950	0,974	0,948	0,908	0,912	0,935	0,910
PO	0,991	0,991	0,996	0,991	0,951	0,951	0,956	0,951
PPC	0,881	0,894	0,943	0,893	0,846	0,858	0,905	0,857
Q	0,991	0,991	0,996	0,991	0,955	0,955	0,957	0,955
RA	0,990	0,990	0,995	0,990	0,951	0,951	0,956	0,951
RP	0,988	0,988	0,994	0,988	0,903	0,910	0,932	0,906
SI	0,978	0,979	0,989	0,978	0,883	0,897	0,923	0,888
SMCT	0,992	0,992	0,996	0,992	0,953	0,954	0,957	0,954
TE	0,800	0,800	0,909	0,833	0,932	0,932	0,947	0,932
VI	0,986	0,986	0,993	0,986	0,948	0,948	0,954	0,948
VS	0,919	0,937	0,961	0,924	0,941	0,941	0,950	0,942
WSH	0,926	0,935	0,964	0,930	0,925	0,925	0,943	0,926

6. Conclusions

Partial Least Squares Structural Equation Modeling (PLS-SEM), and covariance-based (CB-SEM). This paper is presenting a comparison study between the two methods basing on a case study of the sustainable supply chain innovation model for the Moroccan industrial field during the period of 2020. Section I is dedicated to the conceptual model and the two structural analysis techniques presentation. Section II is explaining the methodology. Section III is consolidating the findings revealed where the CB-SEM technique is performed and consistently compared with PLS-SEM.

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Biography

EL MAALMI A. Ph.D. candidate in Industrial Engineering Science, is a team member of Engineering Sciences Laboratory in National School of Applied Sciences, Ibn Tofail University, Kenitra, Morocco. He earned a State Engineer diploma in Chemical Engineering from Mohammadia Engineering School, Rabat, Morocco. Eng. EL Maalmi has more than six years of experience in various industrial and manufacturing fields (Automotive, Rubber, Semiconductors, and ID and security printing). He is operating as a Manufacturing specialist in the Central Bank of Morocco.

Jenoui K. is one of the assistant professors, and a team member of Laboratory Smartilab in the Moroccan School of Engineering Sciences, Rabat, Morocco. Dr. Jenoui is a state engineer in Transport and Logistics from the National School of Applied Sciences of Tetouan. She got her Ph.D. diplomat in Industrial Science from the National School of Applied Sciences of Kenitra. Dr. Jenoui published several journals and conferences papers in the concern of multi-sourcing supplier's selection and evaluation, evaluation System for Monitoring Suppliers and Controlling Risks in the Hospital Sector. She is leading an ambitious project in modeling, simulation, and optimization of supply chain basing Industry 4.0 technologies and systems.

El Abadi L. Is an associate professor, and team member of the Engineering Sciences Laboratory in the National School of Applied Sciences, Ibn Tofail University. Dr. El Abbadi holds a Bachelor of Science degree in Industrial Engineering from Science Technology Faculty, Fes. She earned her master's degree in industrial management and a Ph.D. in IT, Modeling, and Quality from the same university. Dr. El Abbadi, is performing as a professor researcher in the Informatics, Logistics and Mathematics department, Engineering Sciences Laboratory in National School of Applied Sciences, Ibn Tofail University. She has published more than thirty-four journal and conference papers and accomplished more than six projects related to her field of interest.