Structural Equation Models using Partial Least Squares: an Example of the Application of SmartPLS® in Accounting Research

Abstract

In view of the Accounting academy's increasing in the investigation of latent phenomena, researchers have used robust multivariate techniques. Although Structural Equation Models are frequently used in the international literature, however, the Accounting academy has made little use of the variant based on Partial Least Squares (PLS-SEM), mostly due to lack of knowledge on the applicability and benefits of its use for Accounting research. Even if the PLS-SEM approach is regularly used in surveys, this method is appropriate to model complex relations with multiple relationships of dependence and independence between latent variables. In that sense, it is very useful for application in experiments and file data. In that sense, a literature review is presented of Accounting studies that used the PLS-SEM technique. Next, as no specific publications were observed that exemplified the application of the technique in Accounting, a PLS-SEM application is developed to encourage exploratory research by means of the software SmartPLS®, being particularly useful to graduate students. Therefore, the main contribution of this article is methodological, given its objective to clearly identify the guidelines for the appropriate use of PLS. By presenting an example of how to conduct an exploratory research using PLS-SEM, the intention is to contribute to researchers' enhanced understanding of how to use and report on the technique in their research.

Key words: Structural Equation Models; Minimal Least Squares; SmartPLS®.

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1. Introduction

The literature in the fields of marketing (e.g., Howell, 1987; Bagozzi & Yi, 2012), information systems (e.g., Hardin, Chang, & Fuller, 2008), strategy (e.g., Sarkar, Echambadi, &Harrison, 2001; Agarwal, Sarkar, Echambadi, 2002), organizational behavior (e.g., Edwards, 2001), management (e.g., Shields, 1997; Shields & Shields, 1998; Franke, Kristopher & Edward, 2008; Richardson & Vandenberg, 2005), consumer behavior and psychology (e.g., Bollen & Bauldry, 2011) have customarily used Structural Equation Models - SEM) to investigate different latent phenomena.

Specifically in Accounting, the academy's interest in understanding latent phenomena, such as perceptions, judgments, attitudes, organizational knowledge and cultures, and mainly in measuring its influence on different measures, such as learning, satisfaction and even corporate performance, such as stock prices, has significantly increased in recent decades (Smith & Langfield-Smith, 2004; Bisbe, Batista-Fogueta, & Chenhall, 2007; Henri, 2007), particularly in Behavioral Accounting Research – BAR (Mason & Levy, 2001).

The SEM technique has been used in Accounting research due to the need to overcome some of the limitations of first-generation multivariate techniques, including regressions in Ordinary Least Squares (OLS), predominantly in empirical Accounting literature, being particularly useful for research designs in which a dependent variables turns into an independent variable in subsequent relations (Hair Jr., Black, Babin, Anderson, & Tatham, 2009). In these cases, the relations are traditionally investigated using simultaneous equations (including the two-stage least squares method - 2SLS), which can lead to inconsistencies in the estimators if one or more explanatory variables are correlated with the error term of the equation, known as "simultaneous equation bias" (Gujarati & Porter, 2011).

In addition, in comparison with the OLS regression, the SEM offers a range of advantages, such as: more flexible premises; ability to analyze multiple relationships simultaneously; working with latent variables; analyzing time series data; ability to test non-normal data; test models with many equations as a whole, obtaining global adjustment measures; ability to model the mediating and moderating variables; ability to model error terms; etc. (Xiao, 2013).

In that perspective, for example, the study by Nicolaou, Sedatole and Lankton (2011) can be mentioned, which through the incorporation of moderating effects in the structural model found results that suggest that the background literature, operated through first-generation multivariate techniques, mainly OLS regression, provided an incomplete explanation on how the integration of information systems affects the confidence in interorganizational alliances. Nevertheless, although SEM is frequently used in the international literature, Accounting research have hardly used the variant based on Partial Least Squares - PLS-SEM, largely due to a lack of knowledge on the benefits its use offers (Lee, Peter, Fayard, & Robinson, 2011). Although the PLS-SEM approach is frequently used in survey-based research, this method is the most suitable to model complex relations with multiple relationships of dependence and independence among latent variables (Nitzl, 2014). In that sense, it is very useful for applications in experiments and file data (Lee et al., 2011).

This low use of the PLS-SEM approach is even more surprising in view of the Accounting researchers' increasing emphasis, mainly in Management Accounting, on the need to use the technique, as it permits the development of more holistic models (Hughes & Kwon, 1990; Shields, 1997; Shields & Shields, 1998; Chenhall, 2003).

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283

When compared to the multivariate technique, which is more frequent in Accounting research, OLS regression, which restricts the analysis of the relation between a single dependent variable and a range of explanatory variables in a one-way causal sense, consequently demanding the estimation of separate equations to analyze each hypothetic relation, the PLS-SEM permits estimating equations for the simultaneous analysis of the relation among multiple dependent variables (Lee *et al.*, 2011; Smith, 2014).

In that aspect, departing from the insights by Lee, Peter, Fayard, & Robinson (2011) and Nitzl (2014), who encourage studies focused on the elimination of barriers and, consequently, on encouraging the use of PLS-SEM in Accounting, this study intended to exemplify the use of PLS-SEM in exploratory Accounting studies, using the software SmartPLS˚.

Like with any statistical tool, PLS-SEM requires that researchers have considerable knowledge on the method applied, as PLS-SEM comes with several details that, if not treated correctly, can lead to incorrect conclusion, which can obviously cause severe problems for the future development of the theory (Nitzl, 2014). Hence, the main contribution of this study is methodological, given its objective to clearly identify the guidelines for the appropriate use of PLS. By explaining the development of an exploratory research using PLS-SEM, the intention is to contribute to the researchers' enhanced understanding of how to use and report on the technique in their studies.

Besides this Introduction, this study is divided in four topics. Initially, in the Theoretical Background, a short general context of the PLS-SEM approach is presented, together with a literature review of Accounting studies that used the technique for data analysis. Next, in the third topic, the methodological aspects are discussed. In the fourth topic, an example is presented of the application of a reflexive measuring scale. Finally, in the last topic, the final considerations are presented, evidencing the research limitations and indicating opportunities for future research.

2. Theoretical Background

2.1 General context of PLS-SEM approach

The SEM is a set of multivariate statistical technique that permit the simultaneous investigation of a set of theoretical relations among one or more independent variables, with continuous or discrete variables, and one or more dependent variables, also continuous or discrete (Tabachnick & Fidell, 1996). Combining aspects of factorial analysis with multiple regression, the SEM enables the researcher to simultaneously investigate multiple relations of dependence and independence among latent variables, by means of observed variables, as one of the most recent multivariate techniques used in the Social Sciences (Hair Jr, Hult, Ringle, & Sarstedt, 2014).

In Table 1, an overview is presented of the general particularities among Covariance-based SEM - CB-SEM), PLS-SEM and Ordinary Least Squares Regression (OLS):

Table 1

Aspects of CB-SEM, PLS-SEM and OLS Regression techniques

Criteria	CB-SEM	PLS-SEM	OLS Regression
Main software used	LISREL, EQS, AMOS, Stata and MPLUS.	SmartPLS, PLSGraph, NEUSREL and WarpPLS.	SPSS, SAS, Excel, Stata and Minitab.
Objective of general analysis	Assess whether the null hypothesis of the proposed model is plausible, rejecting null hypotheses of specific paths without effect.	Reject the null hypothesis of a set of specific paths.	Reject the null hypothesis of a set of specified relationships.
Objective of variance analysis	Global adjustment model according to the data, represented by several adjustment indices.	Explained variance (e.g. high R^2).	Explained variance (e.g. high R^2).
Estimation technique	Maximum likelihood (ML) is the most used.	Ordinary Least Squares.	Ordinary Least Squares.
Type of maximization	Maximizes the reproduction of the covariance among the variables.	Maximizes the prediction of original gross scores.	Maximizes the prediction of original gross scores.
Specification of construct	Supports the use of reflexive and formative measures for the constructs.	Supports the use of reflexive and formative measures for the constructs.	The measures are combined using a scale, index or other weighting schemes.
Dependent variables	Supports multiple dependent variables.	Supports multiple dependent variables.	A single dependent variable can be assessed.
Mediation test	Mediating variables are tested as part of the comprehensive model.	Mediating variables are tested as part of the comprehensive model.	Separate multistep model to test mediating variables (e.g., Baron & Kenny, 1986).
Premises	Multivariate normal distribution and independent observations (parametric).	Non-parametric.	Multivariate normal distribution and independent observations (parametric).
Data source	Primary data.	Primary and secondary data.	Primary and secondary data.
Sample size	Small samples may not converge, but large samples can introduce bias in the goodness-of-fit statistics.	Large samples do not entail bias in the statistics.	Large samples do not entail bias in the statistics.

Source: adapted from Chin & Newsted, 1999, Gefen, Straub, & Boudreau, 2000; Lee *et al.*, 2011.

It can be noted that, in some aspects, the PLS-SEM approach converges with the OLS regression (e.g. in the objective of the variance analysis, estimation technique, maximization type, data source and sample size). Nevertheless, the CB-SEM is invariably closer to OLS Regression than to PLS-SEM (e.g. with regard to the premises). Although the method based on the Covariance Matrix (CM) is the most disseminated to conduct the SEM, the PLS-SEM has shown to be a frequently used alternative, mainly because it is more flexible with regard to the dimensioning of the sample and because of the lack of suppositions on the data distribution (therefore, it is known as soft modeling) (Nitzl, 2014). The philosophical distinction between CB-SEM and PLS-SEM is relatively simple. If the objective of the research is to test the theory, that is, its confirmation, the appropriate method is CB-SEM. In contrast, if the objective is theoretical development, PLS-SEM is the appropriate choice (Hair, Ringle, & Sarstedt, 2011). Conceptually, PLS-SEM is similar to the use of multiple regression analysis. Its main objective is to maximize the explained variance in the dependent construct and to assess the quality of the data based on the characteristics of the measuring model (Hair Jr. *et al.,* 2014).

The PLS-SEM is called "Partial Least Squares" because the parameters are estimated by means of a series of least squares, while the term "partial" derives from the iterative estimation procedure of the parameters in blocks (per latent variable), to the detriment of the entire model, simultaneously (Lee *et al.*, 2011).

In SEM, the measuring of the phenomenon, not directly observable as a rule (latent construct), occurs through indicators that serve as proxies of the latent variable of interest. Thus, through the combination of several items in a scale, the abstract concept of interest can be measured indirectly (Hair Jr. *et al.*, 2009).

In the path models, diagrams are used to visually exhibit the hypotheses and theoretical relations among variables. In Figure 1, the latent constructs are represented by circles or ellipses (Y1 till Y4), the indicators (observed or manifest variables) are represented by rectangles (x1 till x10). The relations among the constructs and between indicators and constructs are represented as arrows. In PLS-SEM, the arrows always point in a single direction, representing a directional relationship. Arrows pointing in a single direction are considered a predictive relation and, in case of a strong theoretical foundation, they can be interpreted as causal relationships. Finally, the error terms (*e.g.,* e_7 or e_8), reflexively linked to the endogenous construct, represent the non-explained variance when the path models are estimated (Hair Jr. *et al.*, 2014).

Also according to Figure 1, a PLS path model consists of two elements: structural model (also called inner model in the context of PLS-SEM), which evidences the relations (paths) between the constructs; and the measuring models (also referred to as outer models in PLS-SEM), which refers to the relations between the constructs and the indicating variables (rectangles) (Hair Jr. *et al.*, 2014).
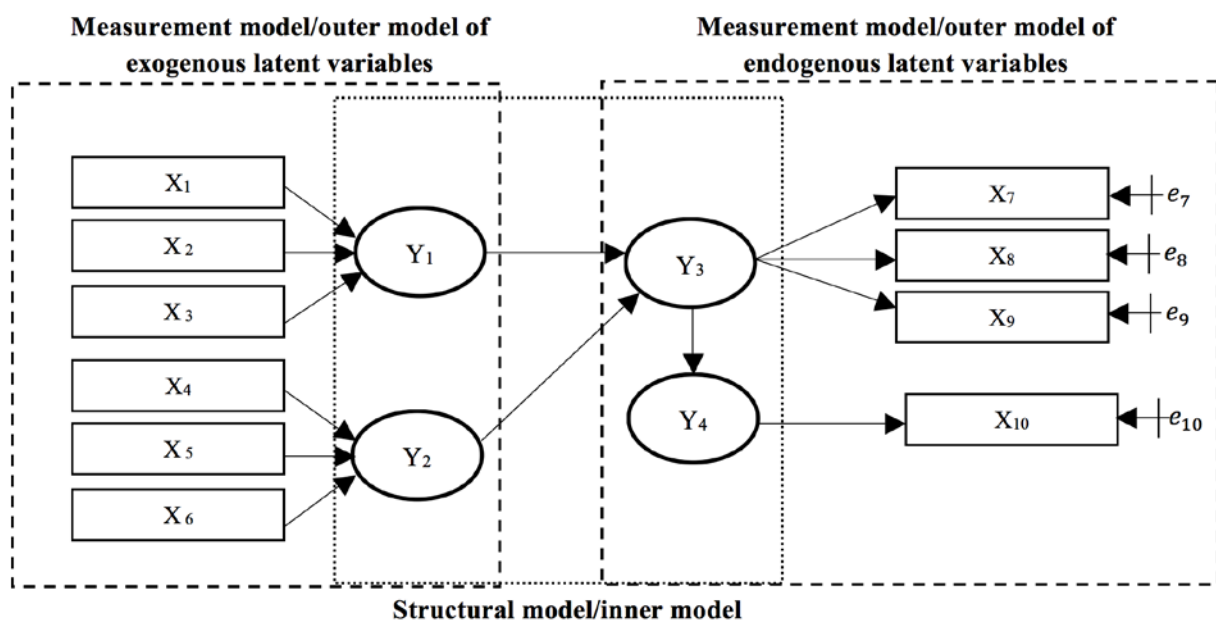
Source: adapted from Hair Jr. *et al.,* 2014.

Figure 1. An example of a path model

The Measuring theory specifies how the latent variables (constructs) are measured. Two types of measuring scales exist in SEM: reflexive or formative. The reflexive indicators, typical of psychometric models, such as the Classical Test Theory (CTT) and the Item Response Theory (IRT), are the most used in the literature. In this type of approach, the sense of "causality" goes from the latent variable to the indicators, that is, the latent construct "causes" the observable items (Hair Jr. *et al.*, 2014). In Accounting research, these indicators would capture perceptions, learning and judgments for example, which are latent construct, normally considered as causes of manifested behavior or of performance scores measured in simulated decision tasks (Rodgers & Guiral, 2011).

In the formative scales, the latent variables are considered "effects" to the detriment of "causes". In this approach, the non-observable construct results from the occurrence of several items that represent a better and more complete image (Rodgers, 1999). To give an example, "liquidity" is a theoretical construct consisting of observable variables, such as the Current Liquidity Index (CLI), Immediate Liquidity Index (ILI), General Liquidity Index (GLI), among others (Rodgers & Guiral, 2011). Studies that require the use of file data (such as management accounting, capital market and management research) demand the use of formative factors (Rodgers & Guiral, 2011).

A path model of PLS consists of two elements. Initially, there is a structural model, also called inner model, in which the relations (paths) between the constructs are exhibited. The second element, the measuring model, also known as outer model, exhibits the relations between constructs and indicators (rectangles) (Hair Jr. *et al.*, 2011). The estimation of the model offers empirical measures of the relations between the constructs (structural model) and between the indicators and constructs (measuring models). The empirical measures permit comparing the structural models with the theoretically established reality. Hence, the fitness of the theory to the data can be determined. Differently from the CB-SEM approach, there is no single goodness-of-fit criterion for the PLS-SEM. Hence, it is important to acknowledge that the quality of the fitness presents distinct meanings in contexts of CB-SEM and PLS-SEM (Hair Jr. *et al.*, 2014).

The fitness statistics in CB-SEM derive from the discrepancy between the empirical and theoretical covariance matrix (Hair Jr. *et al.*, 2009), while the PLS-SEM departs from the discrepancy between the observed (in case of manifest variables) or approximate values (in case of latent variables) of the dependent variables and the values forecasted by the model in question (Hair Jr.*et al.*, 2011). Consequently, using PLS-SEM, the researchers depend on measures that indicate the predictive capacity of the model to judge its quality. More precisely, the assessment of the resulting structural and measuring models in PLS-SEM rests on a set of non-parametric assessment criteria, using procedures like bootstrapping and blindfolding (Hair Jr. *et al.*, 2014).

In this respect, the assessment of Measuring models (relations between the indicators and constructs) involves: composite reliability; variance extracted; indicator reliability; and discriminant validity in case of reflexive models; and variance extracted; collinearity between indicators; and the importance and relevance of external weights in formative models. The assessment of the structural model (relations between constructs), on the other hand, considers: the determination coefficients (R^2); predictive relevance (Q^2), size and significance of path coefficients, effect sizes (f^2) and (q^2)(Hair Jr. *et al.*, 2014).

The composite reliability is used to assess whether the sample is truly free from bias or if the responses – on the whole – are reliable. Composite reliability coefficients between 0.60 and 0.70 are considered appropriate in exploratory studies, while coefficients of 0.70 and 0.90 are considered satisfactory for the other types of research (Hair Jr. *et al.*, 2014). The variance extracted is the extent to which a measure is positively correlated with alternative measures of the same construct. To establish the variance extracted, the researcher considers the external loadings of the indicators and the Average Variance Extracted - AVE. The AVE is the part of the data of the variables explained by each of the respective latent constructs or, in other words, the average extent to which the variables are positively correlated with their respective constructs (Ringle, Silva, & Bido, 2014). Thus, when the AVE is superior to 0.50, it is admitted that the model converges to a satisfactory result (Fornell & Larcker, 1981).

High external loadings in the same construct indicate that the associated indicators have a lot in common with the phenomenon the latent construct captures. This characteristic is known as indicator reliability. The external loadings of all indicators should be statistically significant. Therefore, standardized values with external loadings superior to 0.708 are expected. Indicators with external loadings between 0.40 and 0.70 should only be eliminated if the procedure entails increased reliability and the composite reliability superior to the suggested minimum value (Hair Jr. *et al.*, 2011).

The discriminant validity measures that a construct is truly distinct from the others through empirical standards. Hence, the establishment of discriminant validity implies that the construct is unique and captures phenomena the other constructs in the proposed model do not understand. The main form of assessing the discriminant validity is by confronting the square roots of the AVE coefficients of each construct with the (Pearson) correlations between the other latent constructs (Fornell and Larcker criterion). Discriminant validity will exist if the correlations between the latent variables are inferior to the square root of the AVE (the indicators have a stronger relation with their VL than with other VL (Hair Jr. *et al.*, 2014). Finally, the determination coefficient (R^2), predictive relevance (Q^2) and effect sizes (f^2) and (q^2), criteria to assess the structural model in PLS-SEM (Hair Jr. *et al.*, 2014), will be discussed further on in topic four.

2.2 Short review of Accounting studies that used PLS-SEM

In the past 21 years, some studies have been developed in which the PLS-SEM approach was used as the data analysis technique. Concerning the journals that most publish studies using this type of approach, relevant Accounting journals are observed in the international context, such as Accounting, Organizations and Society (AOS), Management Accounting Research (MAR), The Accounting Review (TAR) and International Journal of Accounting Information Systems (IJAIS), in which 8, 4, 3 and 3 articles were published, respectively.

Studies related to the following subareas are emphasized: performance and remuneration; Cost/ Management Accounting; leadership and behavioral aspects; and Management Information Systems. Finally, samples of different dimensions are highlighted, ranging from 569 observations (Dowling, 2009) to extremely small samples of 18 observations (Anderson, Hesford, & Young, 2002). In Table 2, some Accounting studies are listed that used PLS-SEM as the data analysis technique.

Table 2

Accounting studies that used PLS-SEM as the data analysis technique

Study	Journal	Research objective	Sample size
Cohen, Pant, & Sharp (1994)	Behavioral Research in Accounting (Bria)	Investigate the behavioral determinants of auditors' aggressiveness in relations with clients.	62
Ittner, Larckert & Rajan (1997)	The Accounting Review (TAR)	Examine the effect of financial and non-financial performance measures on annual bonus contracts of CEO's.	317
Rodgers (1999)	Journal of Economic Psychology (JEP)	Assess the influence of perceived economic and management risk on judgment and decision making.	268
Vandenbosch (1999)	Accounting, Organizations and Society (AOS)	Investigate the use and perceived importance of management support information systems for organizational competitiveness.	344
Anderson, Hesford, & Young (2002)	Accounting, Organizations and Society (AOS)	Examine the determinant factors (external environment, processes and team dynamics) of the successful implementation of Activity Based Costing - ABC.	18
Chenhall (2004)	Behavioral Research in Accounting (Bria)	Analyze the role of behavioral conflicts in the implementation of ABC Costing.	56
Hartmann (2005)	Abacus (ABA)	Assess the relation between task uncertainty, environmental uncertainty and tolerance of bias in accounting performance measures.	250
Chenhall (2005)	Accounting, Organizations and Society (AOS)	Examine how the informational dimensions underlying strategic performance measuring systems (SPMS), such as the Balanced Scorecard, influence the desired organizational results.	80
Pennington, Kelton, & DeVries (2006)	Journal of Information Systems (JIS)	Analyze the effect of stress on intentions to use Audit Command Language – ACL technology.	43
Bouwens & van Lent (2006)	Journal of Management Accounting Research (JMAR)	Relation between performance measures and cash bonuses.	151
Mahama (2006)	Management Accounting Research (MAR)	Investigate the relations between the two control management systems (performance measuring systems and socialization processes) and cooperation and how this relationship turns into performance in strategic relations with suppliers.	73
Naranjo-Gil & Hartmann (2006)	Journal of Management Accounting Research (JMAR)	Analyze the relation between management team characteristics and management accounting systems.	99
Naranjo-Gil & Hartmann (2007)	Accounting, Organizations and Society (AOS)	Investigate how the heterogeneity of the management team directly and indirectly affects strategic change through the conception and use of the management accounting system.	103

Study	Journal	Research objective	Sample size
Hall (2008)	Accounting, Organizations and Society (AOS)	Analyze how the comprehensive performance measuring systems (PMS) affect management performance.	83
Elbashir, Collier, & Davern (2008)	International Journal of Accounting Information Systems (Ijais)	Investigate the relation between corporate intelligence systems and organizational performance.	347
Homburg & Stebel (2009)	Management Accounting Research (MAR)	Analyze the determinants of contract clauses between accounting service companies and their clients.	76
Chapman & Kihn (2009)	Accounting, Organizations and Society (AOS)	Analyze the associations between the integration of information systems, budgetary use (control), perceived success of the system and business unit performance.	169
Hall & Smith (2009)	Accounting, Organizations and Society (AOS)	Investigate the relation between mentioning and turnover intentions in public accounting companies.	107
Hartmann & Slapničar (2009)	Accounting, Organizations and Society (AOS)	Assess the relation between the subordinate's trust in superiors and the formality of the performance assessment process.	160
Dowling (2009)	The Accounting Review (TAR)	Analyze the factors that influence the appropriate use of audit support systems by auditors.	569
Abernethy, Bouwens, & Van Lent (2010)	Management Accounting Research (MAR)	Investigate the effects of the leadership style on three elements of the corporate management control system (delegation choice, planning and control systems and the performance measuring system).	128
Diaz & Loraas (2010)	International Journal of Accounting Information Systems (Ijais)	Assess, in the post-adoption period of a technology, the relation between expected learning efforts and the intention to use the technology.	69
Elbashir, Collier, & Sutton (2011)	The Accounting Review (TAR)	Analyze the influence of organizational control related to knowledge management and resource development in the assimilation (strategic integration and use) of business intelligence systems (BI).	347
Nicolaou, Sedatole, & Lankton (2011)	Contemporary Accounting Research (CAR)	Examine if and how the integration of information systems (IIS) affects the trust in inter-organizational alliances.	116
Kallunki, Laitinen, & Silvola (2011)	International Journal of Accounting Information Systems (Ijais)	Assess the effects of the adoption of corporate resource planning systems on the management and financial and non-financial performance control systems of a company.	70
Chong & Mahama (2014)	Management Accounting Research (MAR)	The impact of the budget use style on the team level motivation and team efficacy.	186
Lau & Roopnarain (2014)	The British Accounting Review (BAR)	The effects of non-financial and financial measures on employees' motivation to participate in the definition of objectives.	149

Source: survey by the authors.

Hence, the PLS-SEM approach not only offers a range of advantages in comparison with the first-generation multivariate techniques, being very flexible in terms of the premises and sample dimensioning; but also presents some similarities with OLS Regressions. Accounting researchers have recently used it, with publications in relevant journals.

In addition, it is once again highlighted, as briefly discussed in the Introduction, that the occasional ignore of the relations of dependence and independence between the variables of the model under analysis in the OLS models, the non-control of the direct and indirect effects in the relations of dependence/independence and the non-incorporation of moderating or mediating effects in the structural model potentially makes it more difficult to fully understand the phenomenon of interest.

Hall and Smith (2009), for example, modeled indirect effects in the relation between mentoring and turnover intentions in public accounting companies, observing that the "contradictory" effects related to mentoring (which could serve to increase or reduce the turnover) derived from the fact that they were almost exclusively examined through direct effect models, providing inconsistent results. Nicolaou, Sedatole and Lankton (2011), then, incorporated moderating effects in the structural model and found distinct results from what had been reported in the literature thus far.

In that respect, in view of the Accounting academy's increasing interest in understanding latent phenomena, and mainly in measuring their influence on different measures, such as learning, satisfaction, efficiency and efficacy of corporate performance information systems, the PLS-SEM approach has revealed to be a suitable and extremely relevant data analysis technique for the current Accounting research agenda.

3. Method

To encourage the development of exploratory studies using SEM, the investigation of graduating students' satisfaction will be simulated, as an example of a latent variable, by means of a study using Smart-PLS®. In this fictitious example, the construct Satisfaction (SAT), a dependent variable, is explained by the constructs proposed by Nascimento, Bernardes, Sousa and Lourenço (2015), that is, "Initiatives to Promote Quality" (IPQ), "Scientific Education" (SE) and "Information Support for Students" (ISS). For the four constructs, seven-point Likert scales indicating increasing levels of agreement are used, with score 1 corresponding to I completely disagree and score 7 to I completely agree, while the remaining scores indicate intermediary levels of agreement.

All constructs were measured by means of five items, according to the orientations of Bido, Silva, Souza, & Godoy (2009) which, based on simulations, recommend the use of at least five indicators per latent variable. Another important observation is related to the minimum number of observations per indicator. According to Bentler & Chou (1987), at least five cases should be used per estimated parameter. The conceptual model (structural model) is displayed in Figure 2.
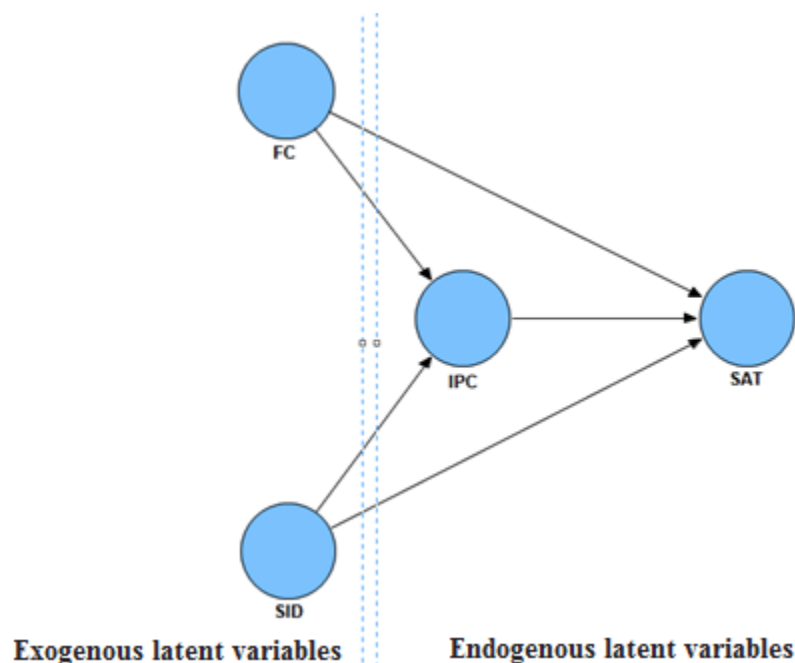
Source: developed by the authors.

Figure 2. Structural model proposed

In this structural model, IPQ simultaneously serves as a dependent (endogenous) and independent (exogenous) variable, as it is explained (arrows pointing towards it) by other latent constructs "Scientific Education" (SE) and "Information Support to Students" (ISS) – and also explains the SAT construct, which is placed in the middle of the model in this case (the exogenous variables only originate arrows, that is, they are not "constituted" inside the model, like the SE and ISS constructs).

Although the PLS approach is acknowledged for its ability to deal with small samples, that does not mean that this is not a relevant concern. The literature suggests that samples of less than 100 observations should be avoided, setting 200 observations as a good starting point (Hoyle, 1995). In this sense, as the base used in this study consists of 440 observations, that is a sufficient number to develop the study. The SEM analysis via PLS does not accept missing values. Therefore, treatment is needed, like adjustments by the average for example. Another important aspect is the analysis of multivariate outliers, which should be properly verified.

The choice of the SmartPLS software is justified because it is the most frequently used nowadays, and mainly because it is available free of charge to students and researchers. Despite this common use, the amount of didactical material available on the software remains limited, mainly because it is relatively recent (developed in 2005) (Wong, 2013). To obtain an academic license, a registration should be completed on the developer's website (www.smartpls.de). In this study, version 2.0 was used.

As presented earlier, in view of the objective to encourage the use of PLS-SEM in Accounting research, next, a reflexive measuring scale will be applied, which is the most recurrent in the literature and the most similar to multiple regression, a multivariate technique commonly used in accounting literature (Lee *et al.*, 2011), by means of SmartPLS®.

4. Data Analysis

### 4.1 Exploratory Factor Analysis

Before performing the SEM procedure, it is important to assess the measures of the constructs, especially the one-dimensionality of the scale - if the items converge to a single construct (Andrade, Tavares, & Valle, 2000). To this end, Exploratory Factor Analysis (EFA) was used separately for each reflexive construct (the use of EFA is valid exclusively for reflexive measuring models, i.e. it does not apply to formative measuring scales), given the interest in evaluating the relationship of each variable with its specific factor. The principal components method was used, adopting the eigenvalue criterion equal to one (1) to extract the factors used. As the existence of correlation between the constructs was expected, we opted for the use of oblique rotations (oblimin direct), which extracts factors considering the covariance between the constructs (Field, 2009).

In the IPQ construct, the Kaiser-Meyer-Olkim (KMO) coefficient of 0.814, superior to the floor of 0.50, and the value of the Chi Square test statistic of Bartlett's test corresponding to 967.991, significant at 0.000, indicates the existence of good fit of the EFA. Relating to commonalities, i.e. the common variance ratio of each item explained by the factor, the items had a mean of 0.63 with a minimum value of 0.57, superior to the floor of 0.50. The solution with extraction of one (1) factor showed an explained variance of 63.04%, also higher than the minimum value reported in the literature, that is, 60% (Hair et al., 2009). The value of 0.853 for Cronbach's Alpha concluded the satisfactory level of internal consistency of the scale (Field, 2009), while the average correlation of 0.58, statistically significant at 0.01, indicated the existence of intermediate colinearity between the indicators of the construct.

The constructs SE (KMO 0.771, 965.124 significant at 0.000, average communality of 0.6052, explained variance of 63.93 with extraction of one factor, Cronbach's alpha of 0.822 and 0.604 average correlations significant at 0.01), ISS (KMO 0.833, 1020.083 significant at 0.000, average communality of 0.6292, explained variance of 60.05 with extraction of one factor, Cronbach's alpha of 0.855 and average correlations of 0.64 significant at 0.01) and SAT (KMO 0.785, 1067.116 significant at 0.000, average communality of 0.6293, explained variance of 60.05 with extraction of aonefactor, Cronbach's alpha of 0.844 and 0.6467 average correlations significant at 0.01) also presented values superior to those recommended in the literature. Thus, it is concluded that the scales are suitable to apply the SEM procedure.

4.2 SEM via Smart PLS

To create a new project, access File, New, and then Create New Project. On the screen open, include the name of the project, called Base here (Step 1) (do not deselect the option import indicator data), click on Next and select the file in its location of origin, clicking on the asterisk (Step 2). It should be highlighted that SmartPLS only supports text files with figures separated by commas (.csv). Finally, after selecting the file (.cvs), click on Finish.
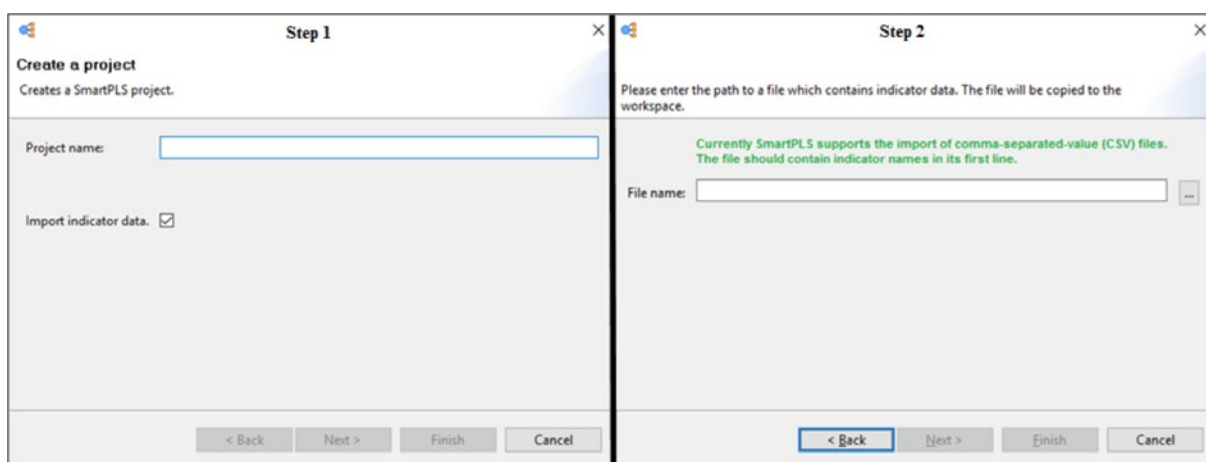
Source: outputs of SmartPLS® v. 2.0.

Figure 3. Steps to create a project and import the database

After concluding the importation of the database, the software presents a screen with three areas. The first marks the project (A), the second the indicators imported (B); and, finally, the model window, where the structural model can be "drawn" (C), as presented in Figure 4 (Part 1). Before starting the process, it is important to verify whether the base has been validated. Therefore, in the Project area, click on the + sign (next to the project name) and then double click the csv file, according to Figure 4 (Part 2):
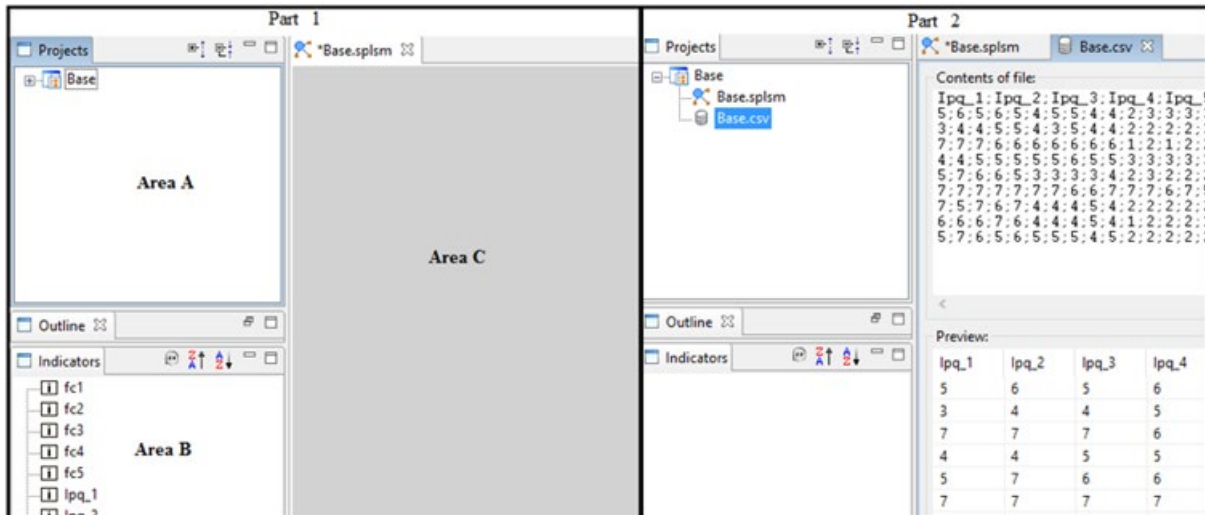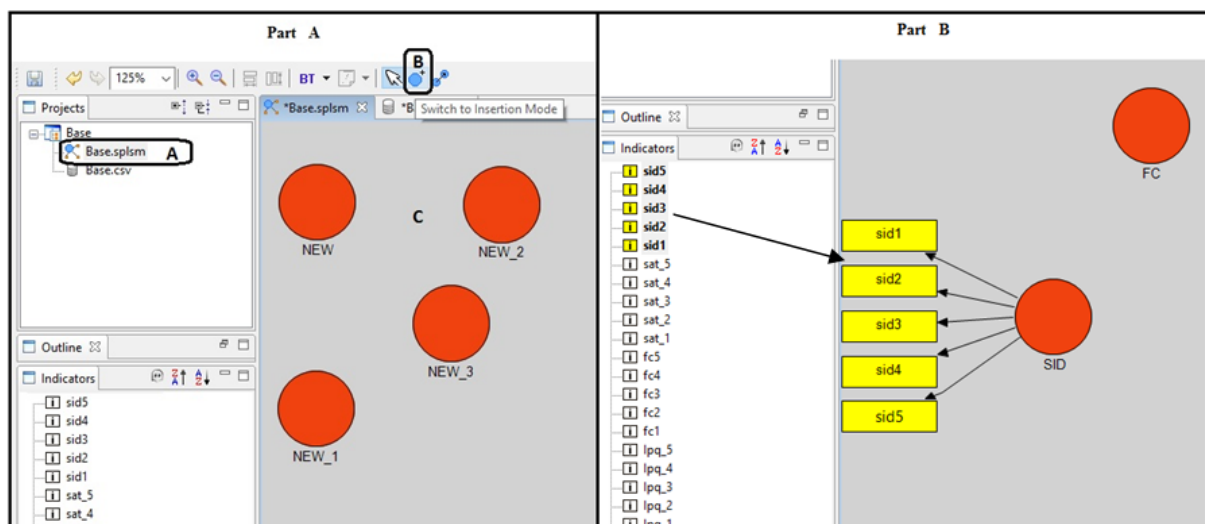
Source: outputs of SmartPLS® v. 2.0.

Figure 4. SmartPLS interface and database validation screen

In the right corner, in "choose delimiter", click on "Semicolon" and then "validate". If there are no problems with the database, the program will issue a message "The data file is valid!". Once the validation of the database has been concluded, the structural model is designed. Therefore, click in the window Base. splsm (mark A), then the button "switch to insertion mode" (mark B) and, finally, click in the design area.

It is important to highlight that each click inserts a latent construct. Hence, working with four latent constructs, four clicks are needed (mark C), as evidenced in Figure 5 (Part A). The next step is to name each construct, clicking on each of the circles and then pressing F2. Then, the indicators should be linked to their respective latent constructs. Thus, press the key Shift, click on the first indicator, then on the next and draw the selection to the respective latent construct. To give an example, the item interval sid1-sid5 is part of the latent construct ISS, as shown in Figure 5 (Part B):

Source: outputs of SmartPLS® v. 2.0.

Figure 5. Insertion of latent construct and indexation of indicators to the constructs

The indicators already linked to some construct are marked in yellow, while the remainder stays white. After linking all indicators with their respective latent constructs, it is important to organize the data visually. To give an example, press the right mouse button on the latent construct to alter on which side the items are presented, as shown in Figure 6 (Part A). Next, click on the button "switch to connection mode" (mark B) (procedure shown in Figure 6 – Part B) and link the circles, thus establishing the relations between the latent constructs.
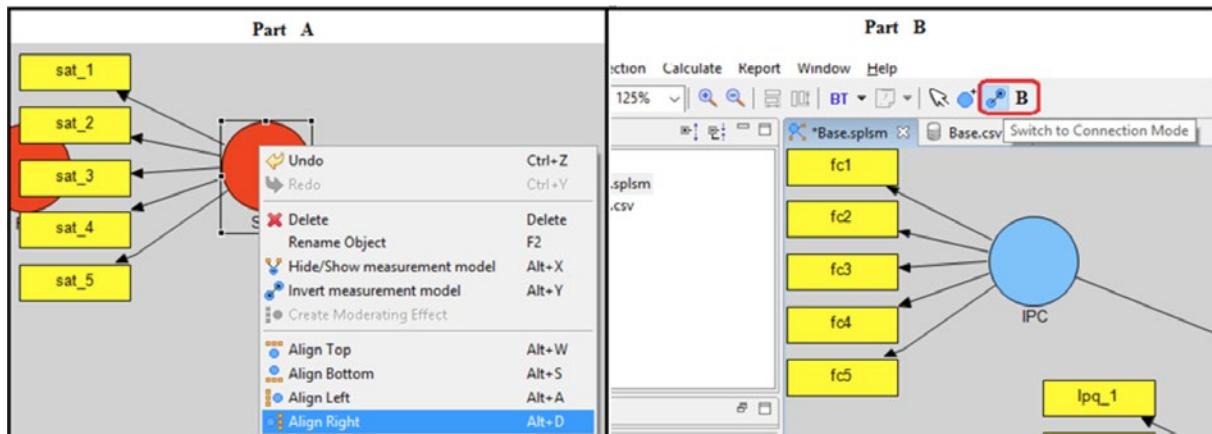
Source: outputs of SmartPLS® v. 2.0.

Figure 6. Change of item positions and establishment of relations between constructs

After concluding the connection process between the latent construct, Path-Modeling estimation is applied, accessing the option 'Calculate' followed by 'PLS Algorithm', according to Figure 7, (Part A). The traditional analysis configuration is the standard in SmartPLS®. Thus, it is sufficient to press "Finish" (Figure 6, Part B).
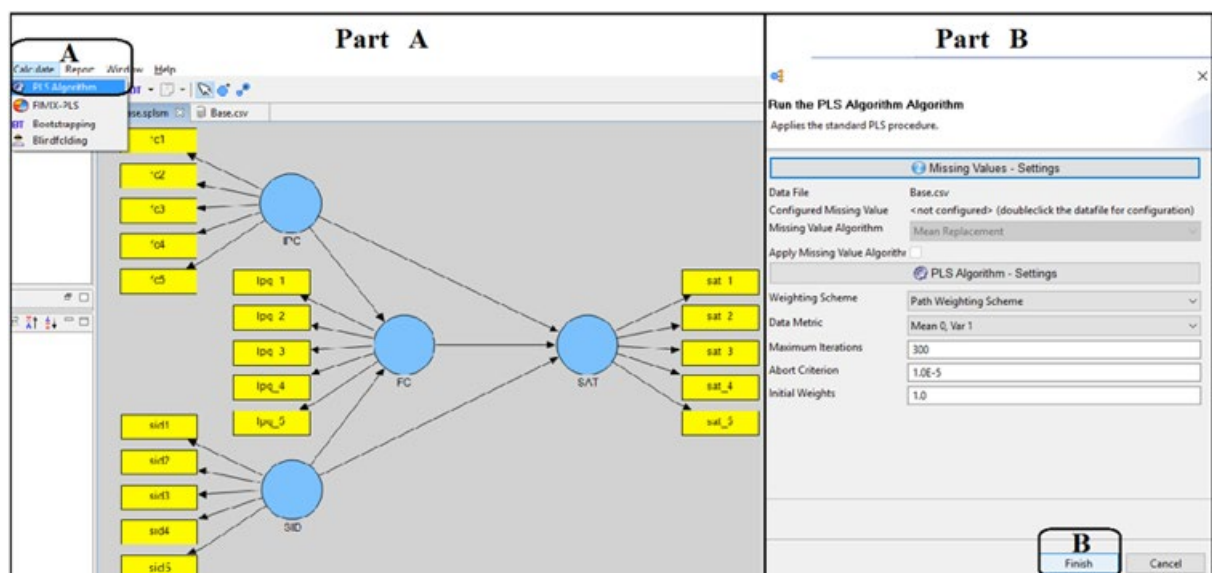
Source: outputs of SmartPLS® v. 2.0.

Figure 7. Path-Modeling Estimation using PLS Algorithm

After exemplifying how to create and estimate a PLS path model, we will now focus on assessing the quality of the results. As presented earlier, this process is divided in two phases: assessment of measuring model and structural model. Initially, the model assessment focuses on the measuring model. As the example used involves a reflexive measuring scale, the composite reliability, variance extracted, indicator reliability and discriminant validity will be assessed. In SEM, the composite reliability is used to replace Cronbach's Alpha (Bagozzi & Yi, 1988). To obtain the composite reliability, access: PLS =>Calculation Results =>Quality Criteria =>Overview. As the coefficients (0.8828, 0.8941, 0.8937 and 0.8970 for SE, IPQ, SAT and ISS, respectively), are much higher than the minimum of 0.6, it can be concluded that high levels of internal consistency exist in the latent variables. If the measuring model were formative, this indicator would not be reported.

To calculate the indicator reliability, the loadings need to be squared (available in: PLS =>Calculation Results=>Outer Loadings). Therefore, an electronic worksheet should be used (to transport the data between the applications, select the values in SmartPLS® and paste them in the worksheet). In Table 3, the loadings and respective reliability coefficients are indicated. To give an example, item IPQ_1 presented a factor loading of 0.8451. The squaring of this coefficient (0.84451^2) results in a reliability indicator of 0.73119.

Table 3
Reliability indicator

Construct	Itens	Loadings	Reliability	Construct	Itens	Loadings	Reliability
IPQ	IPQ_1	0.8551	0.73119601	SE	FC1	0.8877	0.78801129
	IPQ_2	0.7918	0.62694724		FC2	0.7708	0.59413264
	IPQ_3	0.8176	0.66846976		FC3	0.7084	0.50183056
	IPQ_4	0.7632	0.58247424		FC4	0.7648	0.58491904
	IPQ_5	0.7311	0.53450721		FC5	0.7372	0.54346384
SAT	SAT_1	0.9163	0.83960569	ISS	SID1	0.8956	0.80209936
	SAT_2	0.7671	0.58844241		SID2	0.796	0.633616
	SAT_3	0.7445	0.55428025		SID3	0.7478	0.55920484
	SAT_4	0.7822	0.61183684		SID4	0.7281	0.53012961
	SAT_5	0.7412	0.54937744		SID5	0.8108	0.65739664

Source: developed by the authors using data from SmartPLS® v. 2.0.

The analysis of Table 3 shows that all indicators present individual reliability coefficients superior to the minimum acceptable level of 0.4 for exploratory studies and close to 0.7 for confirmatory studies (Hulland, 1999). As the objective of the eventual study in theory would be to empirically test the constructs proposed by Nascimento, Bernardes, Sousa and Lourenço (2014), it can be concluded that reliable indicators exist. To verify the convergent validity, the average variance extracted (AVE) of each latent variable is verified. Therefore, access: PLS =>Calculation Results =>Quality Criteria =>Overview. As all AVE coefficients (0.6025, 0.6287, 0.6287 and 0.6365 for SE, IPQ, SAT and ISS, respectively), are superior to the acceptable limit of 0.5 (Bagozzi & Yi, 1988), it is concluded that convergent validity exists.

The square root of the AVE of each latent variable is used to determine the discriminant validity. As presented earlier, it is concluded that discriminant validity exists when this coefficient (square root of AVE) is higher than the correlation coefficient between the latent variables (Fornell & Larcker, 1981). For this assessment, a table needs to be created with the correlations between the latent variables (obtained based on the section "Latent Variable Correlation", PLS=>Quality Criteria=>Latent Variable Correlations) and the square root of AVE, which is calculated manually and reported in bold in the diagonal of the table. Table 4 presents the square AVE coefficients of each construct and the correlations between the latent variables:
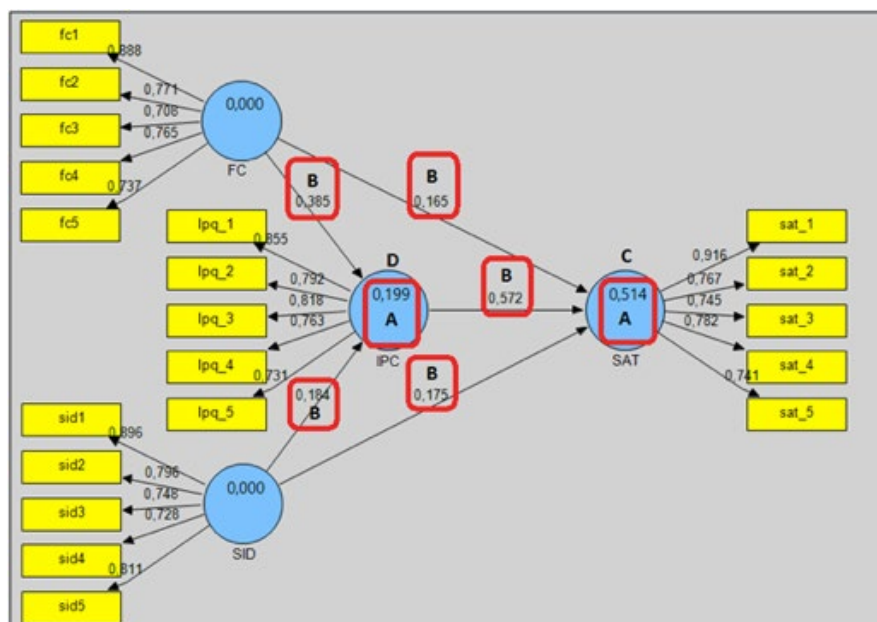
Table 4
Discriminant validity

	SE	IPQ	SAT	ISS
SE	**0.776209**			
IPQ	0.4028	**0.792906**		
SAT	0.4180	0.6788	**0.792906**	
ISS	0.1193	0.2300	0.3260	**0.79781**

Source: developed by the authors using data obtained using SmartPLS® v. 2.0.

The AVE of the latent variable SE found corresponded to 0.6025. Thus, the square root obtained equals 0.776, approximately. As the square AVE's of all latent constructs are superior to the correlation coefficients, it can be concluded that discriminant validity exists.

After concluding the assessment of the measuring model, the next step is to assess the structural model. In this aspect, it is important to report and discuss the determination coefficients (R^2), predictive relevance (Q^2), size and significance of the path coefficients, effect sizes (f^2) and (q^2) (Hair Jr. *et al.*, 2014). In Figure 8, the values inside the circles (mark A) evidence the extent to which the latent variable is explained by the other latent variables in the structural model, while the values on the arrows, called path coefficients (mark B) explain the strength of one construct's effect on the others.

When assessing the degree of explanation of the variance in the endogenous target variable, in this case SAT, the (R^2) corresponded to 0.514 (mark A), which permits concluding that the three latent variables tested (ISS, IPQ and SE) moderately explain 51.4% of the variance in SAT. In combination, the variables SE and ISS explain about 20% of the IPQ variance (mark D). Concerning the sizes and significance of the path coefficients of the inner model, the model suggests that SE presents a stronger inner effect on SAT (0.572), followed by ISS (0.175) and IPQ (0.165). The theoretical relation (path) forecasted between all constructs is statistically significant (standardized path coefficients superior to 0.1).
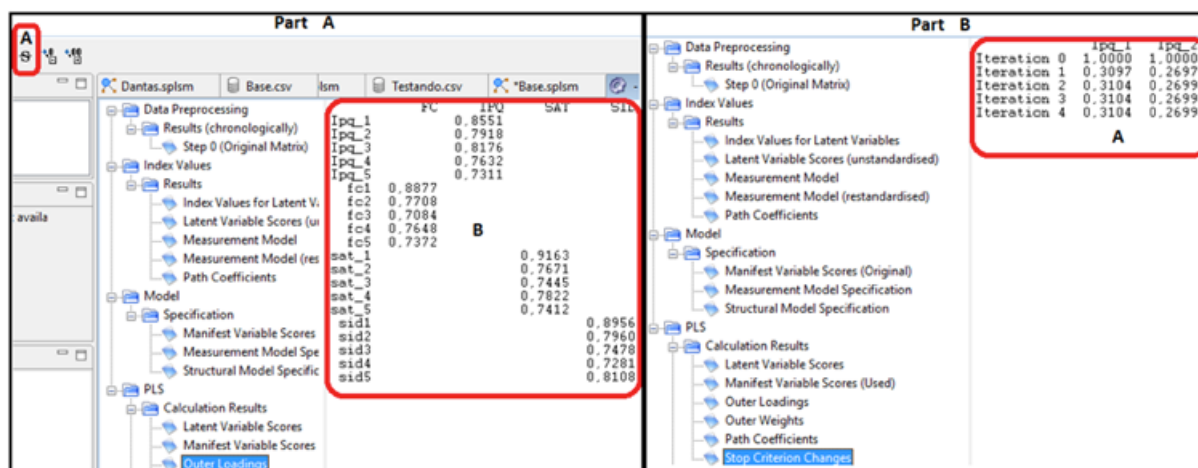

Source: output of SmartPLS® v. 2.0.

Figure 8. Assessment of internal models

REPeC – Revista de Educação e Pesquisa em Contabilidade, ISSN 1981-8610, Brasília, v.10, n. 3, art. 4, p. 282-305, Jul./Sep. 2016

296

Besides reporting the path estimates in the modeling window, SmartPLS® also presents a report based on accessible text through the "Report" menu, and then "Default report". To access the correlations between the latent variable and its respective indicators, as a reflexive model is adopted in this example, the values reported in the "Outer Loadings" (PLS =>Calculation Results =>Outer Loadings) window are analyzed.

For the sake of easier access, press the icon "Toggle Zero Values" (mark A, part A in Figure 9) to remove the extra zeros in the table, thus making it easier to see the path coefficients. If the measuring model were formative, the option "Outer Weights" should be selected. In mark B, part A, Figure 9, the path coefficients estimated in the outer model are reported (the same values reported in Figure 8) for each construct, as presented earlier. According to Hair Jr. *et al.* (2014), the standardized outer loadings should be superior to 0.70. hence, it can be concluded that the loadings and significance of the outer model are superior to the floor reported in the literature.

According to Wong (2013), SmartPLS® concludes the estimation when (whichever happens first): (i) the criterion to interrupt the algorithm is reached; or – (ii) the maximum number of iterations is reached. As the intention is to obtain a stable estimate, the algorithm should conclude the estimation before reaching the maximum number of iterations. To verify whether that is the case, access "Stop Criterion Changes" to determine how many iterations were necessary. The ideal scenario is the conclusion of the estimation before reaching the maximum number of iterations (in this example, the algorithm converged only after four iterations to the detriment of 300, concluding that the estimate is very good, as presented in mark A, in part B of Figure 9).
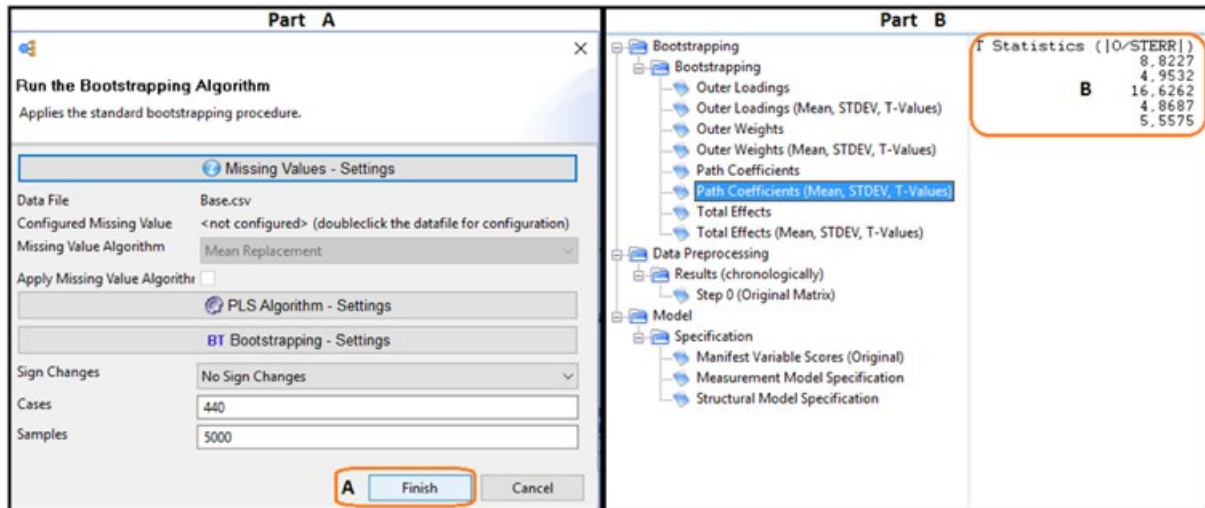

Source: outputs of SmartPLS® v. 2.0.

Figure 9. Path coefficients of outer model and maximum number of iterations of the algorithm

SmartPLS provides "t" statistics to test the significance of the inner and outer models, using a procedure called bootstrapping. In this process, a large number of subsamples (e.g. 5,000) are produced based on the original sample, with replacement, to obtain the standard bootstrap errors, which in turn permit the approximate estimation of "t" values for significance tests of the structural paths (Wong, 2013). For this procedure, access the option "Calculate" and then "Bootstrapping". In SmartPLS, the sample size is known as cases, and the number of subsamples as samples. Thus, as there are 440 valid observations in the database, the number of cases in the Bootstrapping procedure should be increased to 440. After this adjustment, press Finish (mark A, Figure 10, part A).

After concluding the estimation process in the path modeling, the "t" statistics are reported. Thus, coefficients at least higher to 1.96 are expected (5% significance). As many indicators and latent constructs are invariably used in the studies, the display of "t" statistics directly in the modeling window can be impaired. Therefore, SmartPLS publishes a report under Default Report =>Path Coefficients (Mean, STDEV, T-Values). Scroll horizontally until the end, as shown in mark B of Figure 10, part B.

Source: outputs of SmartPLS® v. 2.0.

Figure 10. How to run the bootstrapping and how to obtain the "t" statistics of the constructs

As observed, the values in the column "T-statistics" are superior to 2.57 (significance level = 0.01). The same analysis should be applied to the outer model. Therefore, the values in the window "Outer Loadings (Means, STDEV, T-Values)" should be verified. As all "t" statistics are superior to 2.57, it can be concluded that the loadings of the external model are also highly significant. The next step in the assessment of the structural model is to examine the forecasting skills of the model and the relations between the constructs (Hair Jr. *et al.*, 2014).

Before describing these analyses however, as the estimate of the path coefficients in structural models is based on Ordinary Least Squares (OLS) regressions, as well as on a regular multiple regression, the path coefficients can be biased. Hence, it is important to examine whether collinearity problems exist in the structural model. To develop this assessment in the inner model, the scores of the latent variables (PLS => Calculation Results => Latent Variable Scores) should be used one by one as inputs of a multiple regression (e.g. the score of the SE variable is inserted as dependent and the IPQ, SAT and ISS scores as independent, and so forth). As SmartPLS does not offer this procedure, another statistical package needs to be used. In this example, no multicollinearity problems were observed (minimum 1.057 and maximum 1.966 for VIF).

As presented earlier, concerning the investigation of the structural model, it is important to understand that the PLS-SEM adjusts the model to the empirical data, in the attempt to obtain the best estimates of the parameters by maximizing the explained variance of the latent endogenous variable, thus, to the detriment of applying goodness-of-fit measures, the structural model in PLS-SEM is assessed based on heuristic criteria that are determined by the predictive power of the model (Hair Jr. *et al.*, 2014). In this aspect, it is assumed that the model is specified correctly, as it predicts the endogenous constructs (Rigdon, 2012). Hence, besides assessing the significance of the path coefficients and the level of the R^2 coefficients, it is also important to report and discuss the size of the (f^2) and (q^2) effects and the predictive relevance (Q^2).

Besides assessing the R^2 coefficients of all endogenous constructs, the change in R^2 when an exogenous construct is omitted from the model can be used to assess if the omitted construct substantially affects the endogenous construct of interest (Hair Jr. *et al.*, 2014). That measure is known as the size of the effect (f^2). Chin, Marcolin and Newsted (1996) affirm that the researchers should not only indicate if the relation between the variables is significant, but also report the effect size between these variables, given that it helps the researchers to assess the global contribution of the research. Calculated manually, the f^2 of an endogenous latent variable is obtained by confronting the R^2 included with the R^2 excluded. The R^2 included is the value available in the global model estimate and the R^2 excluded is obtained based on the re-estimation of the model after the exclusion of a specific predecessor (a latent construct) of the proposed model. f^2 is calculated as follows (Hair Jr. *et al.,* 2014):

$$f^2 = \frac{R^2\text{included} - R^2\text{excluded}}{1 - R^2\text{included}}$$

In the path model (Figure 8), SAT presents an R^2 of 0.514, but the $R^2_{excludedSE}$ corresponds to 0.492, the $R^2_{excludedIPQ}$ to 0.251 and the $R^2_{excludedISS}$ to 0.485. Hence, the f^2 calculated equals 0.045, 0.541 and 0.060, for SE, IPQ and ISS, respectively. Hence, considering that f^2 coefficients of 0.02, 0.15 and 0.35 indicate small, small and large effects, respectively (Hair Jr. *et al.,* 2014), it is concluded that the effect of the SE construct is medium, of the IPQ large and of the ISS small.

Besides assessing the magnitude of the R^2 coefficients as a predictive precision criterion, the researchers should also examine Stone-Geisser's Q^2 (validated redundancy measures). More specifically, the procedure predicts the point indicators in the endogenous reflexive measuring models and constructs of a single item (the procedure does not apply to endogenous formative constructs).

The Q^2 coefficients can be calculated by means of the Blindfolding procedure in Calculate=>Blindfolding. In the Blindfolding configuration window, an Omission Distance – OD between 5 and 10 is suggested for most studies (Hair Jr. *et al.*, 2012). However, as the division of the number of observations used in the model by the distance chosen may not result in a whole number (Wong, 2013) and as there are 440 observations in the database used, an OD of 8 can be chosen (resulting in a product of 55). Only the endogenous constructs of the model are selected to execute the blindfolding algorithm. Therefore, only IPQ and SAT are selected.

The first part of the default report (Default Report=>Blindfolding=>Results=>Construct Crossvalidated Redundancy) presents the summary of the total results of the blindfolding procedure (first three lines), followed by the results of each of the eight blindfolding rounds. Chin (1998) suggests that a good model demonstrates relevance when Q^2 is higher than zero. Hence, as all Q^2 coefficients are considerable higher than zero (values reported in column 1-SSE/SSO), it is concluded that predictive relevance of the model exists in relation to the endogenous latent variables.

The Q^2 coefficients estimated by the blindfolding procedure represent a measure of how well the path model can predict the initially observed values. Similar to the approach of the f^2 effect to assess R^2 coefficients, the relative impact of the predictive relevance (q^2) can be obtained by means of a procedure analogue to the calculation of f^2 (Hair Jr. *et al.,* 2014):

$$q^2 = \frac{Q^2\text{included} - Q^2\text{excluded}}{1 - Q^2\text{included}}$$

In Table 5, the Q^2 coefficients included and excluded for each construct and the respective size of the predictive relevance are reported.

Table 5
Assessment of size of predictive relevance

	Q² included	Q² excluded	q² Effect Size	Size
SE	0,3186	0,2931	0,037422953	Small
IPC	0,3186	0,1576	0,236278251	Medium
ISS	0,3186	0,3008	0,026122689	Small

Source: developed by the authors based on data obtained from SmartPLS® v. 2.0.

Thus, based on the reported Q^2 coefficients of each construct, it is concluded that SE, IPC and ISS present small, medium and small effects, respectively (Hair Jr. *et al.,* 2014).

5. Final Considerations

The SEM is described as the second generation of multivariate analysis, offering substantial advantages over the first-generation techniques, such as the principal components analysis, factor analysis, discriminant analysis or multiple regression, due to the researcher's greater flexibility to assess the interaction between theory and data (Chin, 1998). SEM is a fusion of two powerful approaches – factorial analysis and path analysis – which allow the researchers to simultaneously assess the measuring model (traditionally using factor analysis) and the structural model (traditionally using path analysis) (Lee, Peter, Fayard, & Robinson, 2011).

Despite the relevance and mainly the potentials of the SEM technique, the variant based on PLS-SEM has been hardly used in Accounting literature, mainly due to the lack of knowledge on the benefits its use offers. In this sense, departing from the insights by Lee *et al.* (2011) and Nitzl, (2014), this study presented an overview of the PLS-SEM technique, a review of the recent accounting literature that used PLS as a data analysis technique and, finally, exemplified the use of PLS-SEM to conduct exploratory studies by means of SmartPLS®.

Although some important topics could not be elaborated in further depth, the study achieved its objective and, in that sense, represents an important tool for further research, mainly at the graduate level. Despite the potentials of using PLS-SEM for Accounting research, the amount of didactic material available on PLS-SEM, and mainly specific material on SmartPLS is still very incipient (Wong, 2013). This study is relevant by minimizing this gap and encouraging the development of exploratory studies using SmartPLS®, being particularly useful for graduate students.

Therefore, this study is expected to contribute to the researchers' understanding on PLS-SEM and, as such, the technique can be incorporated into the routine of Accounting research. Future studies can be developed to exemplify the use of formative models, second-rank constructs, multilevel analyses, longitudinal frameworks and mainly data without normal distribution, such as dichotomous data. Future studies can also discuss the benefits of using PLS-SEM to replace or complement the first-generation multivariate techniques employed in accounting research.

This study is limited by the fact that it merely exemplifies the application of a reflexive measuring scale, and mainly because it does not address SEM modeling based on covariance.

REPeC – Revista de Educação e Pesquisa em Contabilidade, ISSN 1981-8610, Brasília, v.10, n. 3, art. 4, p. 282-305, Jul./Sep. 2016

300

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301

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303

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