

STRUCTURAL EQUATION MODELING WITH THE SMARTPLS

ABSTRACT

The objective of this article is to present a didactic example of Structural Equation Modeling using the software SmartPLS 2.0 M3. The program mentioned uses the method of Partial Least Squares and seeks to address the following situations frequently observed in marketing research: Absence of symmetric distributions of variables measured by a theory still in its beginning phase or with little “consolidation”, formative models, and/or a limited amount of data. The growing use of SmartPLS has demonstrated its robustness and the applicability of the model in the areas that are being studied.

Keywords: Structural Equation Modeling; SmartPLS; Partial Least Square; Marketing Application.

MODELAGEM DE EQUAÇÕES ESTRUTURAIS COM UTILIZAÇÃO DO SMARTPLS

RESUMO

O objetivo deste artigo é a apresentação de um exemplo de forma mais didática de um da modelagem de Equações Estruturais com o software SmathPLS 2.0 M3. O referido programa usa o método de Mínimos Quadrados Parciais e busca atender situações muito frequentes na pesquisa de Marketing: Ausência de distribuições simétricas das variáveis mensuradas, teoria ainda em fase inicial ou com pouca “cristalização”, modelos formativos e/ou quantidade menor de dados. O uso crescente do SmatPLS vem mostrando a robustez e aplicabilidade do modelo nas pesquisas da área.

Palavras-chave: Modelagem de Equações Estruturais; SmartPLS; Mínimos Quadrados Parciais; Aplicação em Marketing.

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1 INTRODUCTION

The main objective of this article is the didactic presentation of the use of the software SmartPLS in Structural Equations Modeling. This article is not intended to be fully comprehensive on the subject, but rather, presents a beginning for those who intend to use the software and statistic models in their research. For a more comprehensive discussion we recommend the book by Hair et al. (2014).

There are many situations in the applied social and behavioral sciences that are faced with data

that do not adhere to a normal multivariate distribution, need more complex models (many constructs and many variables observed), are formative models (see Figure 1), have “little” data, and/or are models with less consecrated theoretical support. In these situations, covariance based structural equations modeling (CB-SEM) or models based on maximum likelihood estimation (MLE) are not recommended, but rather, variance based structural equation modeling (VB-SEM) or partial least square models (PLS-SEM) are recommended (HAIR et al., 2012).

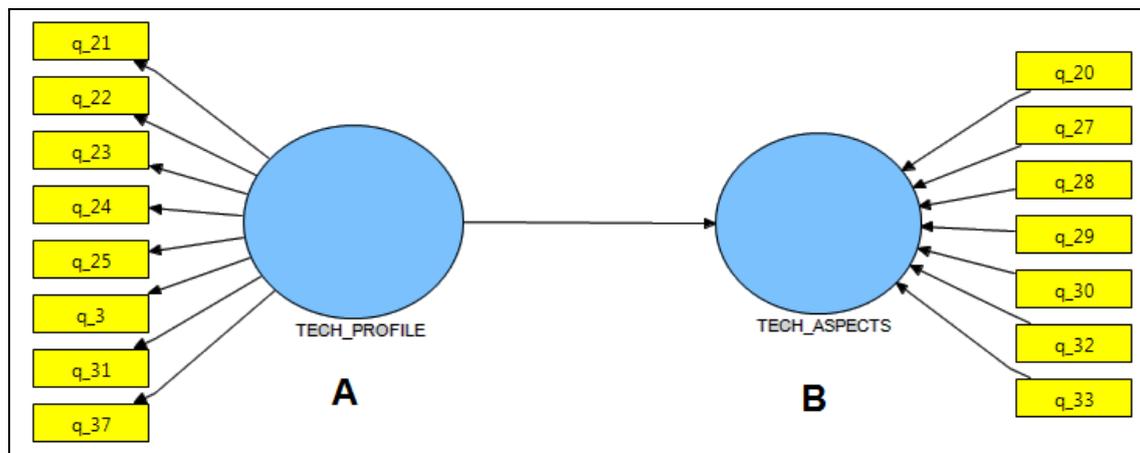


Figure 1 - Hypothetical model indicating two models of distinct measurements: A is reflexive and B is formative (the arrow that links both constructs presents the structural model).

The basic difference between CB-SEM and VB-SEM is in the way they treat data, in a so-called didactic way. In the first case, there are multiple linear regressions realized simultaneously and, in the second, the correlations between the constructs and their measured or observed variables or items (measuring models) are calculated, and linear regressions between constructs (structural models) are made. In this manner, one is able to estimate more complex models with a smaller amount of data. Clarifying further, we will present an example of Structural Equation Models with PLS in the SmartPLS software 2.0 M3. This software is free and can be obtained at the site www.smartpls.de, through a user registry request. After obtaining a login and password, users gain access to a restricted area where there is an interesting

forum with user questions and answers, tutorials, databases to use for practice, and the links to download the program.

For this article, we chose to present an example of a previously published study about questions of environmental marketing, or green marketing, to ensure readers have access to details of the study and, if necessary, can go deeper into the topic. That study (BRAGA JUNIOR et al., 2014) was published in the International Journal of Business and Social Science and is available on the internet free of charge and presents four constructs: Environmental concern IND, Environmental concern Others, Declared purchase IND, and Declared purchase Others (see Figure 2). We even used 421 cases of original databases.

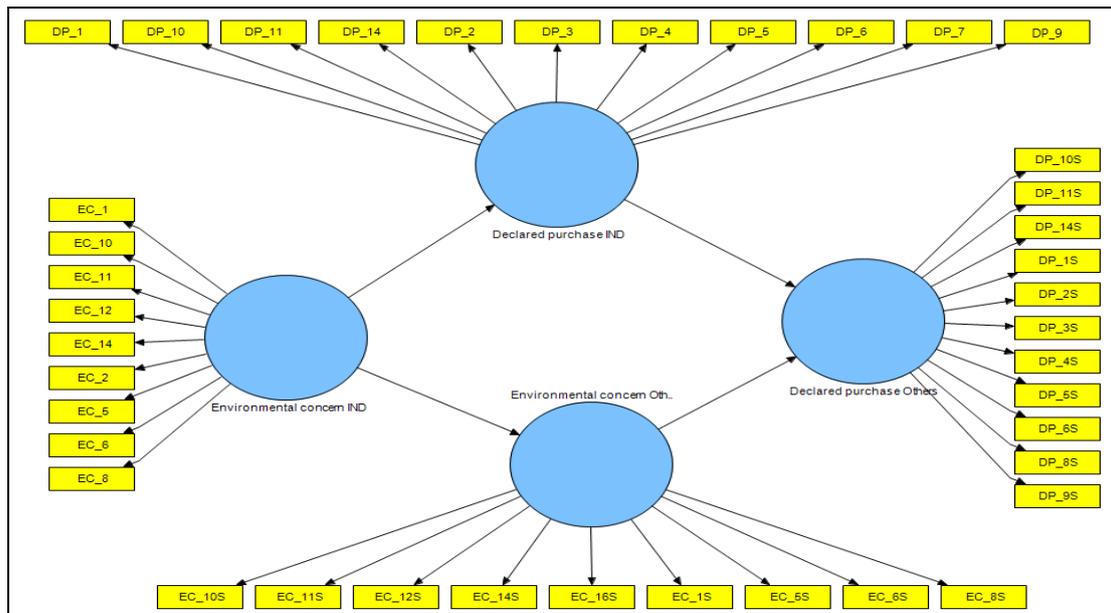


Figure 2 - Initial screen of the example used in the SmartPLS software.
Source: BRAGA JUNIOR et al., 2014

To use the PLS, one must estimate the minimum sample size that will be used. To estimate minimum sample size, you can use software that is free and very practical: G*Power 3.1.9 (<http://www.gpower.hhu.de/en.html>) (FAUL; ERDFELDER; BUCHNER; LANG, 2009). When the data is entered into the software, the latent construct or variable that has the highest number of predictors (receives the largest number of arrows), should be evaluated. For the calculation we observe that there are two parameters: the power of the test (Power=1-

$\beta_{\text{erro prob. II}}$) and the size of the effect (f^2). Cohen (1998) and Hair et al (2014) recommended a power of 0.80, median $f^2 = 0.15$, and that the construct Declared purchase Others has two predictors (has two arrows – see figure 2). Thus, for the PLS, the construct Declared Purchase Others decides the minimum sample to be used. Figure 3 demonstrates the result of the test using the software. Therefore, the calculated minimum sample for the example should be 68 cases, but as a suggestion, in order to have a more consistent model, it is beneficial to double or triple this amount.

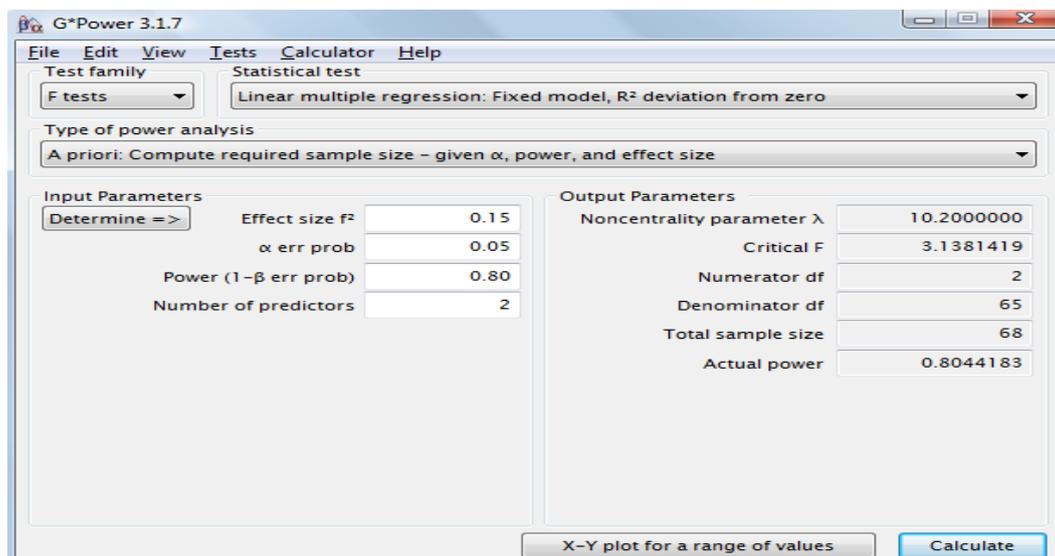


Figure 3 -Screen of the software G*POWER 3.1.9 with the calculation of the minimum sample of the example studied.

After presenting the objective, the software, and the example of use, the next section shows details of using the software.

2 MOUNTING THE MEASURING AND STRUCTURAL MODELS ON THE SMARTPLS

As the PLS is a possibility for the Structural Equation Modeling (SEM), there is symbolism that the reader should become familiar with (see Figure 4):

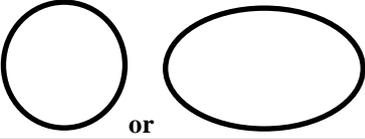
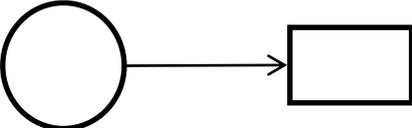
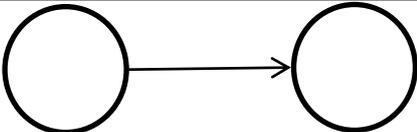
SYMBOL	DEFINITION
	Construct or Variable Latent (LV)
	Variable observed or measured or indicated (OV)
	Correlation between LV and OV (measuring model)
	Causal Relation – Coefficient of the Path between an independent LV → Dependent (structural model)

Figure 4 - the Symbols used for the Structural Equation Models.

Once you have installed the program and see the existing tutorials on the site itself, it is necessary to load the data of the research that will be analyzed using SmartPLS. The best way of doing this is to enter it into an Excel spreadsheet, using the following steps: In the columns there will be the variables and in the lines the respondents or cases; the first line should have the variable labels, taking care to not begin with a number. For example, if the construct has as its name “Declared Purchase”, it would be practical to label the first measured variable or indicator of this construct: DC1. Furthermore, the spreadsheet cannot have formulas, letter codes (only in the labels), or missing data. For missing data, complete any empty cells with a different number than all the rest. For example: 99.

After filling in the labels, you should save the spreadsheet in the format of comma-separated values

(CSV). Take care to eliminate spreadsheets two and three, which are the Excel standard before saving the file.

To create a new project, on the Menu bar use: File → Create New Project. A dialogue window will open and will ask you for the name of the new project. Type the name and click on Next. Another window will open asking you to search for the file “xxx.csv”; click on Next. The next box will be the definition of the “missing values”. Proceed as previously indicated, placing 99 and mark the box to warn that the variable or indicators have missing data. Whenever the software finds a 99 it will eliminate the respondent, in the case that you use the standard default option of the SmartPLS. Figure 5 shows the software and the previously-created project.

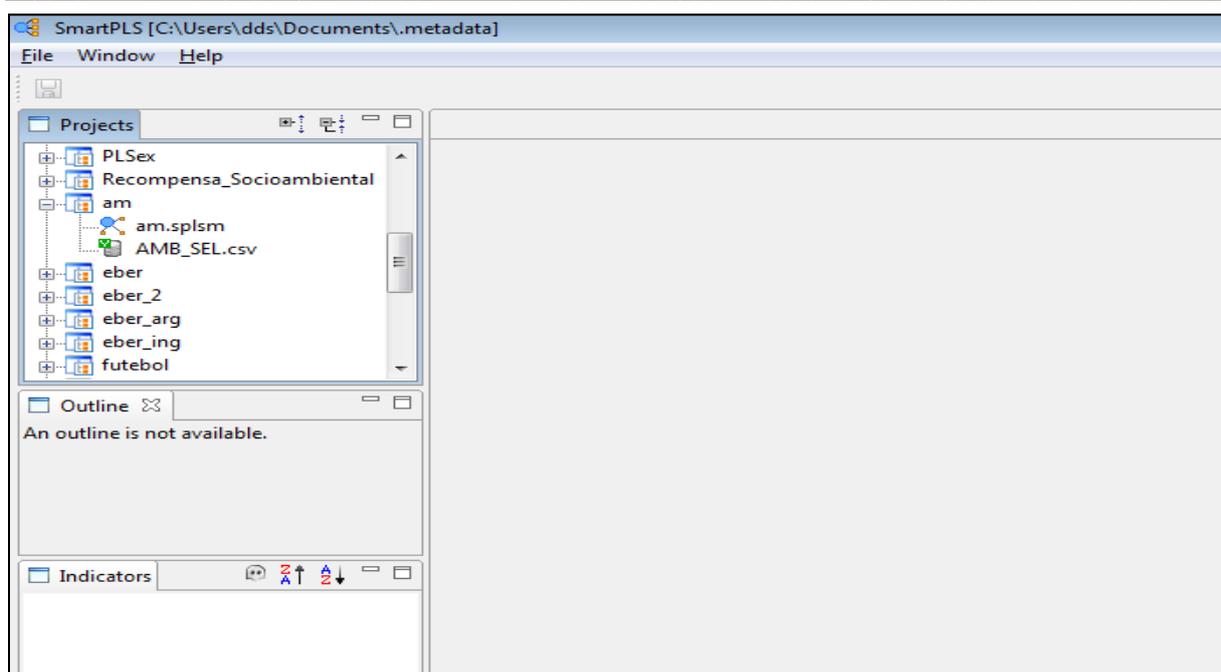


Figure 5 - SmartPLS screen with the “am” project created.

Note that in figure 5, the upper-left-hand side has a window with “Projects” and “am” is there: there are two “files” am.splsm and AMB_SEL.csv with an indication of a “see button” in green, indicating that the data are correct to be used. If there is an indication of “?” in red, the database has a problem and needs to be analyzed. When this problem occurs you should “eliminate the recourse”: right click on the database and choose the option for elimination.

As you click on the database, a window will open on the right hand side of the software (work area). Click on “validate” on the right hand side. A window will appear that says “the data file is valid”;

click on OK and double click on am.splsm. In Indicators (lower left-hand side) the variables will appear (with the labels used in the Excel spreadsheet), as shown in Figure 6 (lower). Also highlighted in this figure are three tools below the Menu Bar – in the center of the screen – The first White Arrow – is the standard mouse cursor; the second circle +, when turned on, allows the mouse to be used as a creation tool for the constructs. This is very easy - just click on the screen under “am.splsm.” The third tool, the two circles linked by an arrow, creates the structural model (the arrows between the constructs).

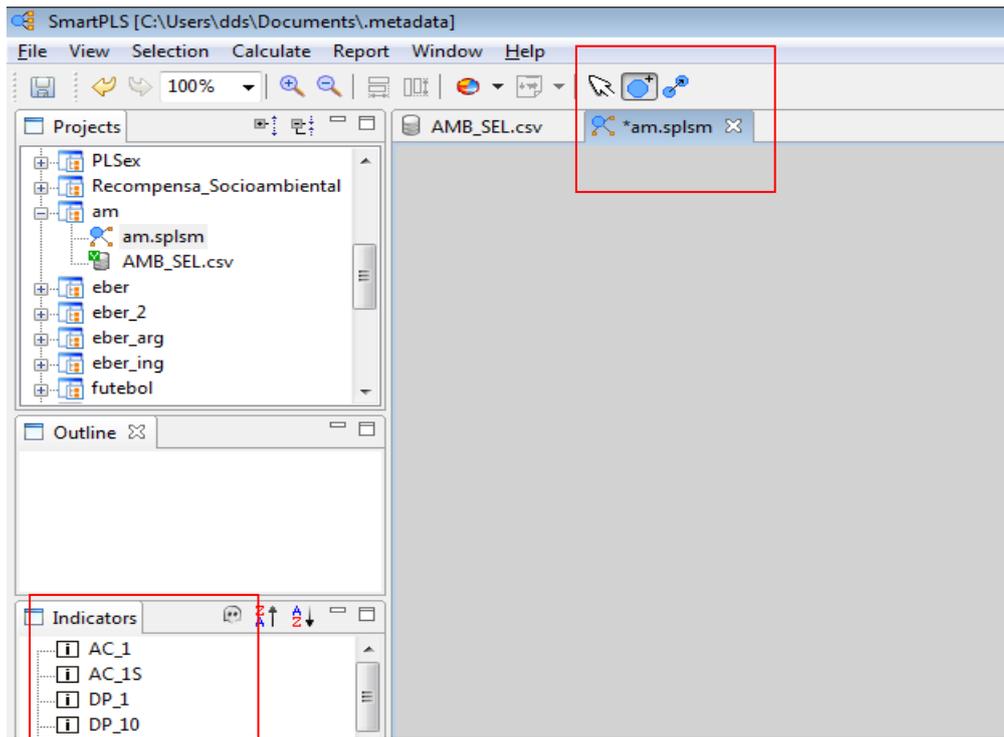


Figure 6 - SmartPLS screen with the tools for the creation of the model and the indicators (OV).

After creating the constructs, to mount the rest of the measuring model, using the white arrow, click and hold on the indicator or OV that corresponds to the construct, drag the OV to the desired construct, and place it on the construct on the screen. Repeat the operation until the model has been completed. To

rename the constructs right click on them and choose "Rename Object". Figure 7 shows the created measuring models. Note that the constructs or LV are in red, because the links between them are missing (creation of the structural models).

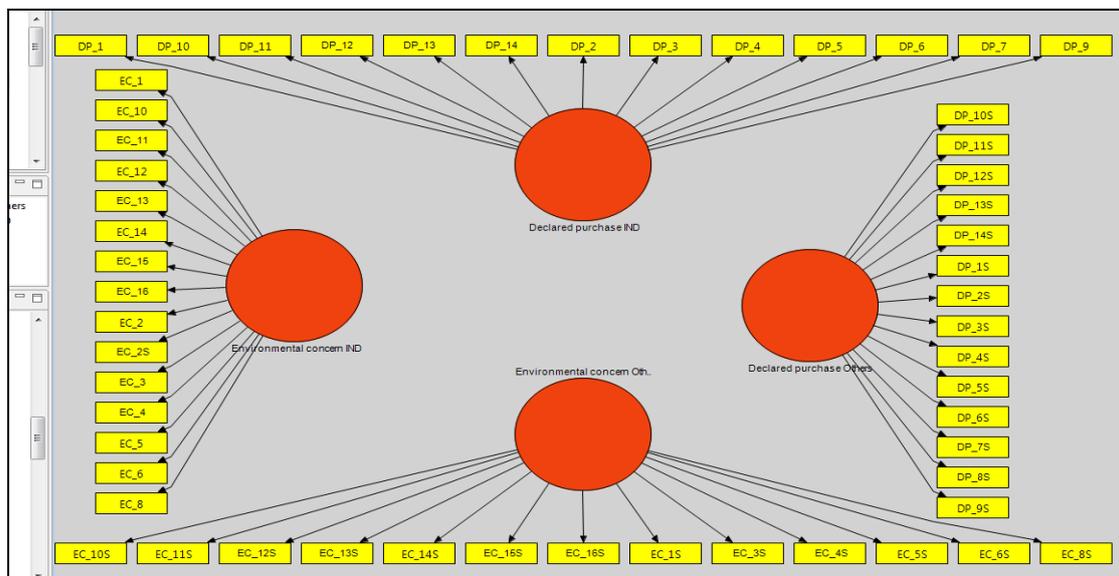


Figure 7 - measuring models of the SEM used.

To create the structural model, turn on the third tool of the design. Click on one of the constructs and move to another construct and click on it. There will be an arrow linking the two. Repeat the process until making all the necessary links (figure 2 shows the initial SEM model completed). Beginning at this point we can start the analyses.

3 RUNNING THE SEM ON SMARTPLS

To run the generated SEM you should use the options below the menu bar (see Figure 8). There are

four options of subprograms that execute different analyses: PLS Algorithm: used to run the main SEM; FIMIX PLS: Finite Mixture PLS (named the non-observed latent or heterogeneity Class techniques): used to detect the presence of groups within the data that have not been controlled; bootstrapping: resampling technique: used to evaluate the significance (p-value) of the correlations (measuring models) and the regressions (structural model); blindfolding: used to calculate the relevance or the Predictive Validity (Q^2) or indicators of Stone-Geiser and the size of the effects (f^2) or Cohen Indicators, which will be discussed further ahead.

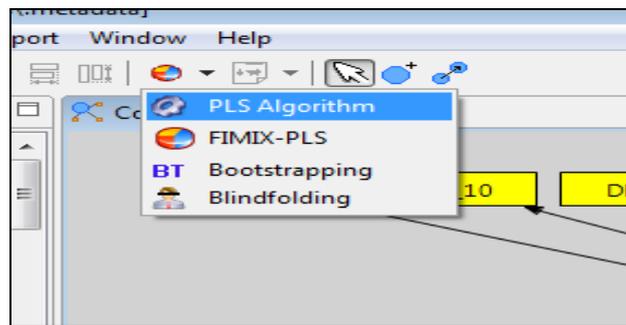


Figure 8 - Options for the data analysis of the SmartPLS.

4 USING THE PLS ALGORITHM

When selecting a PLS Algorithm, a dialogue window is opened with the options for running SEM (see Figure 9). In this window the information about the database will appear (AMB_SEL.csv), the missing

values (99), and the option of running a Missing Value Algorithm (the substitute of the missing data) or case wise replacement (eliminate the respondent or research subject). Case wise replacement is more adequate.

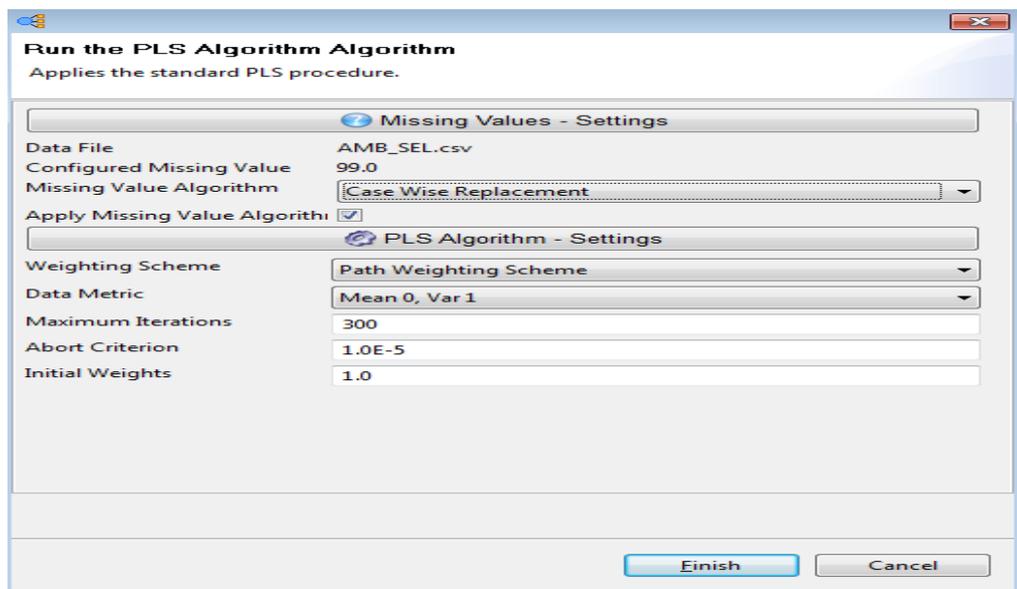


Figure 9 - Dialogue window with the PLS Algorithm.

You also have the option to Apply Missing Value Algorithm. If this option is not marked and there are data missing with the number 99 in that field, the SmartPLS will run SEM considering the value 99 as being a subject answer code. Immediately thereafter there will be PLS Algorithm settings.

In the Weighting Scheme options, there are three other possibilities:
 Path Weighting Scheme – SEM desired (relations among LV are regressions).
 Factor Weighting Scheme – Does an almost factorial confirmatory analysis – (relations among LV are correlated).

Centroid Weighting Scheme (relations among LV consider only signal of the correlations “+/- 1”). The oldest is only used if the others do not converge.

Path Weighting Scheme is the most adequate for the SEM and that is followed by the default values of the model: mean = 0 and standard deviation = 1 (to read the exit values between 0 and 1); maximum number of rotations for the model to converge (300); cutoff criteria (Abort Criterion): when the changes were less than 0.00001. Once the options have been configured, you can click on OK. Immediately the software will supply a figure with the main values (see Figure 10).

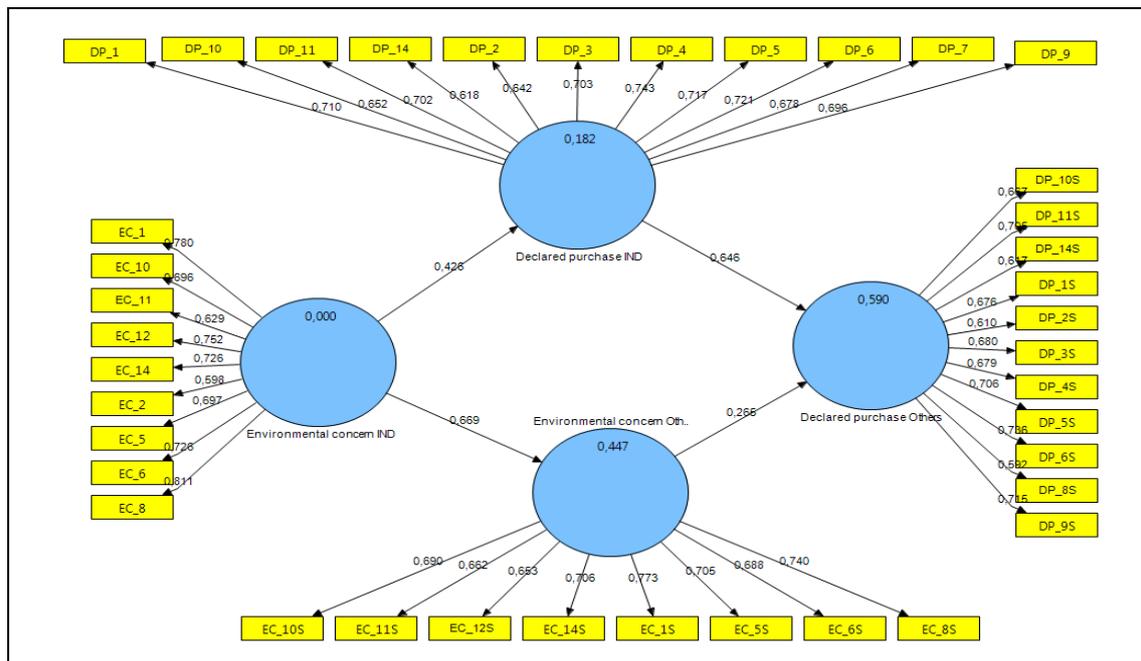


Figure 10 - Screen with the SEM calculation.

Notes: A → Shows the measuring model with the correlated values between the OV and the LV; B → Displays the value of R^2 and C → Shows the coefficient of the Linear Path Regression between LVs.

After having run the SEM you should ask for a report of the results obtained. There are four options below the Menu Bar of the program (see Figure 11). Requesting a report in the HTML format will take you

directly to the hyperlink “PLS Quality Criteria” where you will have a general view of the quality of the adjusted model (see Table 1).

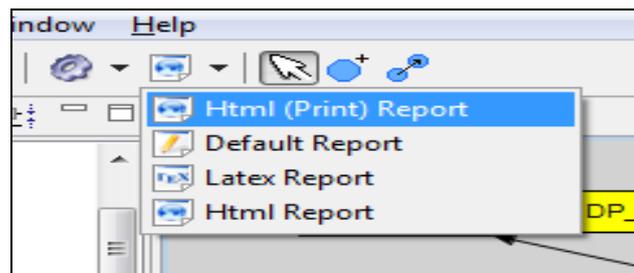


Figure 11 - Options for reports in the SmartPLS.

Table 1 - Values for adjustment quality for the SEM model

	AVE	Composite Reliability	R Square	Cronbachs Alpha
Declared purchase IND	0.476329	0.908909	0.181855	0.889701
Declared purchase Others	0.452393	0.900479	0.589861	0.878519
Environmental concern IND	0.512140	0.903590	-----	0.879153
Environmental concern Others	0.460401	0.886379	0.447328	0.853615

Note: The LV Environmental concern IND does not have an R² value, as it is an independent one or it precedes the others in the SEM.

From this point on the analyses of the adjusted model begins. This is done in two steps: First the measuring models are evaluated, and, after any adjustments, the path models are evaluated (HENSELER et al., 2009; GÖTZ et al., 2010).

In sequence, the first aspect to be observed of the measuring models are the Convergent Validities obtained by the observations of the Average Variance Extracted - (AVEs). Using the Fornell and Larcker (HENSELER et al., 2009) criteria, that is, the values of the AVEs should be greater than 0.50 (AVE > 0.50)

The AVE is the portion of the data (non-respective variables) that is explained by each one of the constructs or LV, respective to their groups of variables or how much, on average, the variables correlate positively with their respective constructs or

LV. Therefore, when the AVEs are greater than 0.50 we can say that the model converges with a satisfactory result (FORNELL & LARCKER, 1981).

The analysis of table 1 shows only one of the two constructs or LV (Environmental concern IND) of the SEM presents an AVE value of > 0.50. In these situations the observed or measured variables should be eliminated from the constructs that have an AVE < 0.50. Figure 12 shows that SEM with seven variables displaced from their original positions (figure 10) and that they present factorial loads of smaller values. Explaining more clearly, the AVE is the average of the factorial loads squared. Therefore, to elevate the value of the AVE, the variables with factorial loads (correlations) of a lower value should be eliminated.

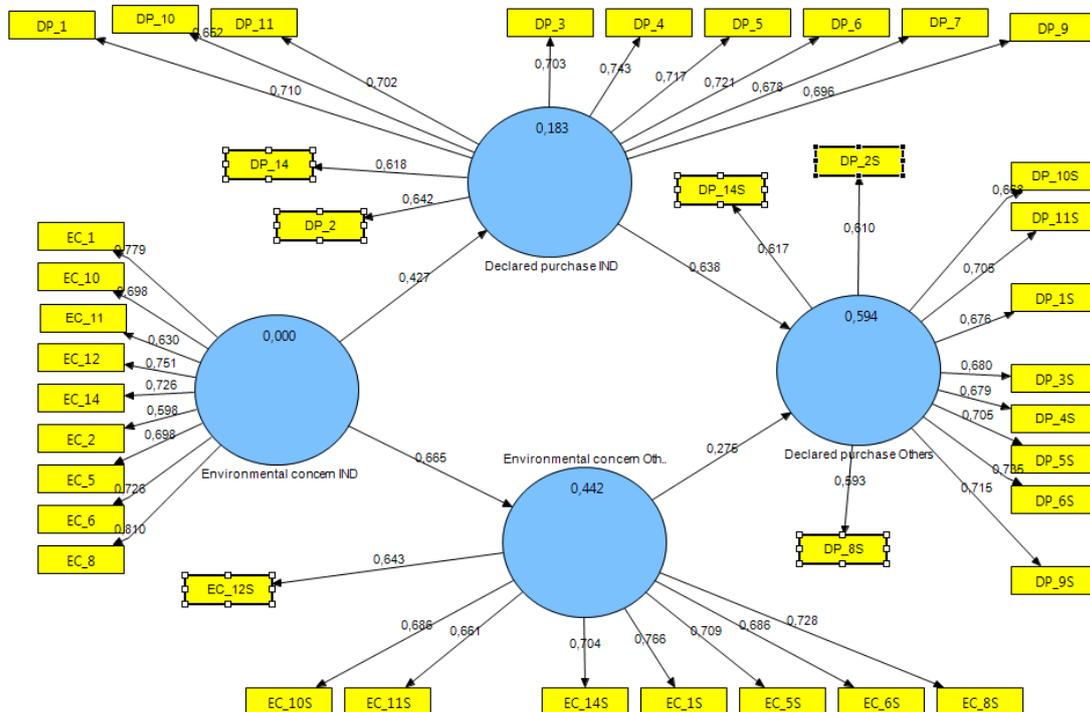


Figure 12 - SEM with smaller OV factorial loads displaced from their original positions to be eliminated.

Eliminating the seven variables, it is possible to achieve all of the AVE values above the 0.50. Table 2 shows the new values for the adjustment quality.

The second step, after guaranteeing the Convergent Validity, is to observe the internal consistency values (Cronbach's Alpha) and the Composite Reliability (CR) (Dillon-Goldstein's ρ - rho). The traditional indicator Cronbach's Alpha (CA), is based on the variables inter-correlations. CR is the most fitting to PLS, as it prioritizes the variables

according to their reliabilities, while the CA is very sensitive to the number of variables in each construct. In the two cases, the CA, as well as the CR, are used to evaluate if the sample is free of biases, or even, if the answers – in their group – are reliable. CA values above 0.60 and 0.70 are considered fitting in exploratory studies and CR values of 0.70 and 0.90 are considered satisfactory (HAIR et al., 2014). Table 2 demonstrates that the CA and CR values are adequate.

Table 2 - Values for the SEM adjustment quality after the elimination of the OVs with lower values for the factorial loads.

	AVE	Composite Reliability	R Square	Cronbachs Alpha
Declared purchase IND	0.503973	0.901293	0.187226	0.876728
Declared purchase Others	0.503923	0.890339	0.613444	0.859257
Environmental concern IND	0.511975	0.903567	-----	0.879153
Environmental concern Others	0.516447	0.881924	0.410175	0.844263

The third step is to evaluate the Discriminant Validity (DV) of the SEM, which is understood as an indicator that the constructs or latent variables are independent from one another (HAIR et al., 2014). There are two ways: observing the Cross Loading – indicators with higher factorial loads in their respective LV (or constructs) than in others (CHIN, 1998) and the criteria of Fornell and Larcker (1981): Compare the square roots of the AVE values of each construct with the correlations (of Pearson) between the constructs (or latent variables). The square roots of the AVEs should be greater than the correlations between the constructs.

Analyzing table 3, it clearly states that the factorial loads of the OVs in the original constructs (LVs) are always greater than the others. In principle, this means the model has discriminant validity based on the Chin criteria (1998); but when the criteria of Fornell and Larcker (1981) (see table 4) is being used

we can note that the model can be improved to guarantee the DV.

The SmartPLS supplies the cross load values in the report. The software removes each OV from the original LV, places it in another LV and recalculates the factorial load, one by one, until the value of all the factorial loads of all the OVs and LVs are determined (see table 3). Therefore, going back to the report, you can remove the correlation between the LV, transfer the data to another program, for example, Excel, in conjunction with the table PLS Quality Criteria, where the AVEs are, to calculate the square roots of their values.

Once the procedures are executed, custom dictates placing the values of the square roots of the AVEs in the main diagonal and highlight them in some other color (in table 4 they are blue). Table 4 shows the respective values.

Table 3 - Values of the cross loads of the OVs and LVs

	DECLARED PURCHASE IND	DECLARED PURCHASE OTHERS	ENVIRONMENTAL CONCERN IND	ENVIRONMENTAL CONCERN OTHERS
DP_1	0.72180	0.576923	0.20493	0.155895
DP_10	0.672085	0.484608	0.419233	0.251031
DP_10S	0.445929	0.690871	0.187339	0.379344
DP_11	0.71432	0.505711	0.36825	0.260965
DP_11S	0.521981	0.707306	0.272026	0.400624
DP_1S	0.548623	0.703118	0.114779	0.238559
DP_3	0.714668	0.512378	0.225885	0.204063
DP_3S	0.485537	0.709823	0.100992	0.321864
DP_4	0.749881	0.557581	0.308289	0.256279
DP_4S	0.495147	0.678226	0.147742	0.353384
DP_5	0.717388	0.500783	0.327335	0.229561
DP_5S	0.524428	0.711556	0.160402	0.356909
DP_6	0.73294	0.572863	0.206102	0.185371
DP_6S	0.557635	0.757346	0.144832	0.326564
DP_7	0.658231	0.422177	0.348771	0.249766
DP_9	0.703294	0.552113	0.343047	0.247553
DP_9S	0.580414	0.718121	0.270548	0.403131
EC_1	0.23894	0.137514	0.779291	0.548169
EC_10	0.392087	0.214182	0.697537	0.400499
EC_10S	0.245859	0.372301	0.40024	0.709685
EC_11	0.449277	0.25552	0.632949	0.369042
EC_11S	0.363434	0.46584	0.462943	0.685941
EC_12	0.237817	0.142616	0.746251	0.45438
EC_14	0.201855	0.099822	0.726439	0.472452
EC_14S	0.136709	0.304167	0.44022	0.710921
EC_1S	0.214948	0.279571	0.587722	0.763044
EC_2	0.395219	0.199236	0.598611	0.324645
EC_5	0.36769	0.220379	0.699297	0.438306
EC_5S	0.218603	0.394551	0.378286	0.721954
EC_6	0.219818	0.112916	0.725467	0.475664
EC_6S	0.190497	0.377169	0.313151	0.7076
EC_8	0.281823	0.211048	0.809348	0.60042
EC_8S	0.213782	0.281892	0.580108	0.728972

The analysis of table 4 shows that the values of the correlation between the LVs Declared purchase IND and Declared purchase Others (0.735263) is slightly larger (≈ 0.025 or 2.5%) than the square roots of the AVEs of these same LVs (0.709911 and 0.709875) (highlighted in bold print in table 4). Generally, being that the values indicated have little

difference, one option could be to leave the model as it is without any alteration, but exaggerating the accuracy, new OVs should be removed. Those variables (one by one) that have smaller differences in the factorial crossed loads should be removed, that is, those OVs that present high correlation values in two constructs (or LVs).

Table 4 - Values of the correlations between LV and square roots of the AVE values in the main diagonal (in blue)

	Declared purchase IND	Declared purchase Others	Environmental concern IND	Environmental concern Others
Declared purchase IND	0.709911			
Declared purchase Others	0.735263	0.709875		
Environmental concern IND	0.432696	0.249814	0.715524	
Environmental concern Others	0.320194	0.491093	0.640449	0.718642

Observing table 3, verifying that the variables DP_1 (difference of the correlation values between the LVs Declared purchase IND and Declared purchase Others = 0.14488), DP_9 (difference of the values of the correlations between the LVs Declared purchase IND and Declared purchase Others = -0.13771). Therefore, you remove them one by one, analyzing the new values of the square roots of the AVEs and the correlations between the constructs and you can meet the criteria of Fornell and Larcker (1981). Table 5 shows the new values for the correlations between LV and the square roots of the AVE values.

With the guarantee of Discriminant Validity, the adjustments of the measuring models have been completed and now we begin to analyze the structural model. The first analysis at this second moment is the evaluation of Pearson's coefficients (R^2): The R^2 evaluates the portion of the variance of the endogenous variables, which is explained by the structural model. It indicates the quality of the adjusted model. For the area of the social and behavioral sciences, Cohen (1988) suggests that $R^2 = 2\%$ as classified as having a small effect, $R^2 = 13\%$ as a medium effect, and $R^2 = 26\%$ as having a large effect.

Table 5 - Values and correlations between the LV and square roots of the AVE values in the main diagonal (in blue), after the removal of new variables in the SEM

	Declared purchase IND	Declared purchase Others	Environmental concern IND	Environmental concern Others
Declared purchase IND	0.72228			
Declared purchase Others	0.69514	0.71770		
Environmental concern IND	0.4366	0.226089	0.71556	
Environmental concern Others	0.324122	0.474623	0.640808	0.71556

Upon removing the OVs from the SEM, the values of R^2 also become altered. Thus, table 6 shows the new values of PLS Quality Criteria. Therefore, we

can see that for the LVs Declared purchase Others and Environmental concern Others, the R^2 are large and for the LV Declared purchase IND, the R^2 is medium.

Table 6 - Quality adjustment values for the SEM model after eliminating the OVs in order to obtain a discriminating validity

	AVE	Composite Reliability	R Square	Cronbachs Alpha
Declared purchase IND	0.521682	0.883949	0.190619	0.846579
Declared purchase Others	0.515092	0.881311	0.552672	0.842816
Environmental concern IND	0.51203	0.903575	-----	0.879153
Environmental concern Others	0.516465	0.881927	0.410635	0.844263

Interpretation of these values show that when respondents think of others, they believe that “there will be more purchased” than when they think of only themselves.

Next, since we are dealing with correlations and linear regressions, we should evaluate if these relations are significant ($p \leq 0.05$). For a correlation case, a null hypothesis (H_0) is established such that $r = 0$ and for a regression case, it is established that $H_0: \Gamma = 0$ (path coefficient = 0). If $p > 0.05$ and H_0 is accepted, then the inclusion of the LVs or OVs in the SEM should be rethought. The software calculates the Student t tests among the original values of the data and those obtained via the technique of re-sampling, for each correlation relation OV – LV and for each relation LV – LV. The SmartPLS presents the values

of the t test and not the p-values. Therefore, one should interpret that for the degrees of freedom, values above 1.96 correspond to p -values ≤ 0.05 (between -1.96 and +1.96 corresponding to the probability of 95% and 5% outside of this interval, in a normal distribution).

In order to test the significance of the cited relations, use the Bootstrapping module (re-sampling technique (see figure 8)). When you select this module, SmartPLS opens a dialogue window to define the parameters of the calculation (see figure 13). For the configuration, Hair et al. (2014) recommends that you use the Missing Value Algorithm for sign changes: Individual changes, use in Cases: number of subjects in your sample (241 in this example), and in Samples (re-sampling): at least 300, 500, or 1000 etc.

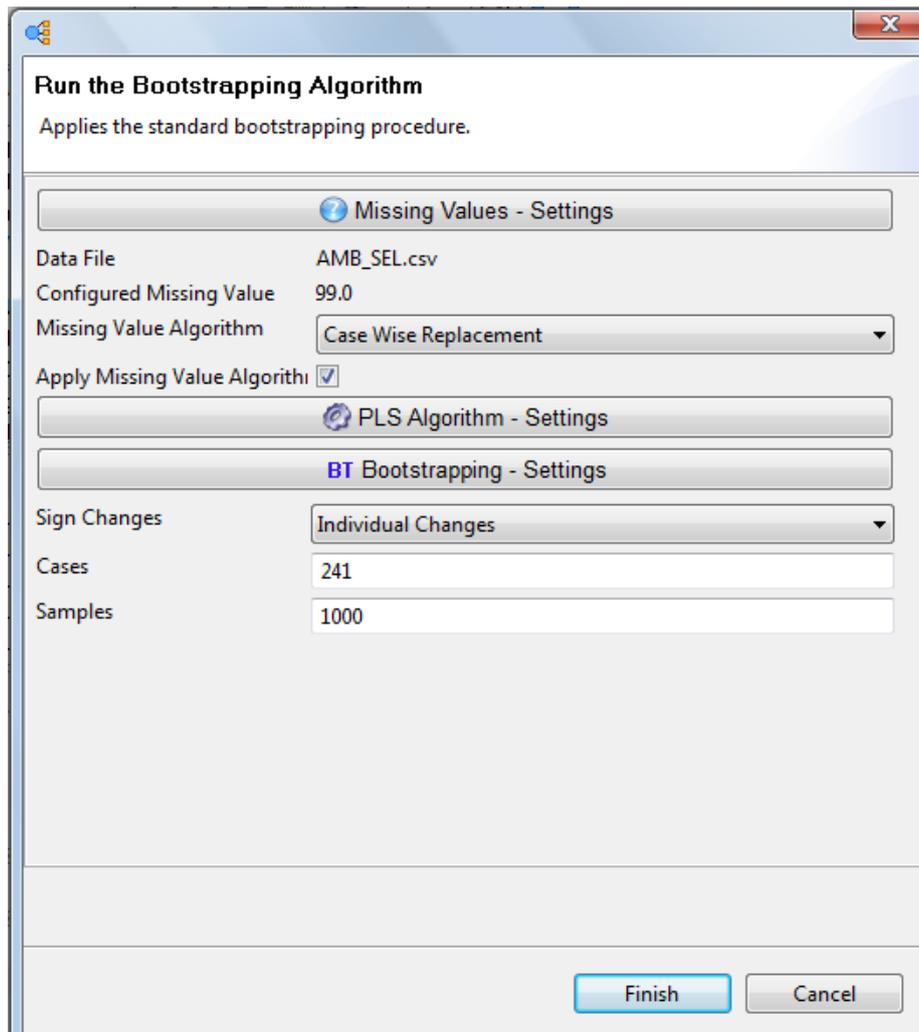


Figure 13 - Window of configuration of the Bootstrapping module of the SmartPLS

After running the Bootstrapping module, a figure will appear on the SEM, now with the test values. These values will also be on the report that can be requested. Figure 14 shows the SmartPLS screen with the values referred to on the t tests. The reading of the figure in question shows that all of the values of the relations OV – LV and LV – LV are above the referenced value of 1.96. In all the cases the H_0 was rejected and you could say that the correlations and

the coefficients of the regression are significant, as they are different than zero. The values of the t tests can be as well, found in the report by the Bootstrapping calculation.

Then, the values of two other indicators of the quality of the model adjustment are evaluated: Relevance or Predictive Validity (Q^2) or Stone-Geisser indicator and Effect Size (f^2) or Cohen's Indicator.

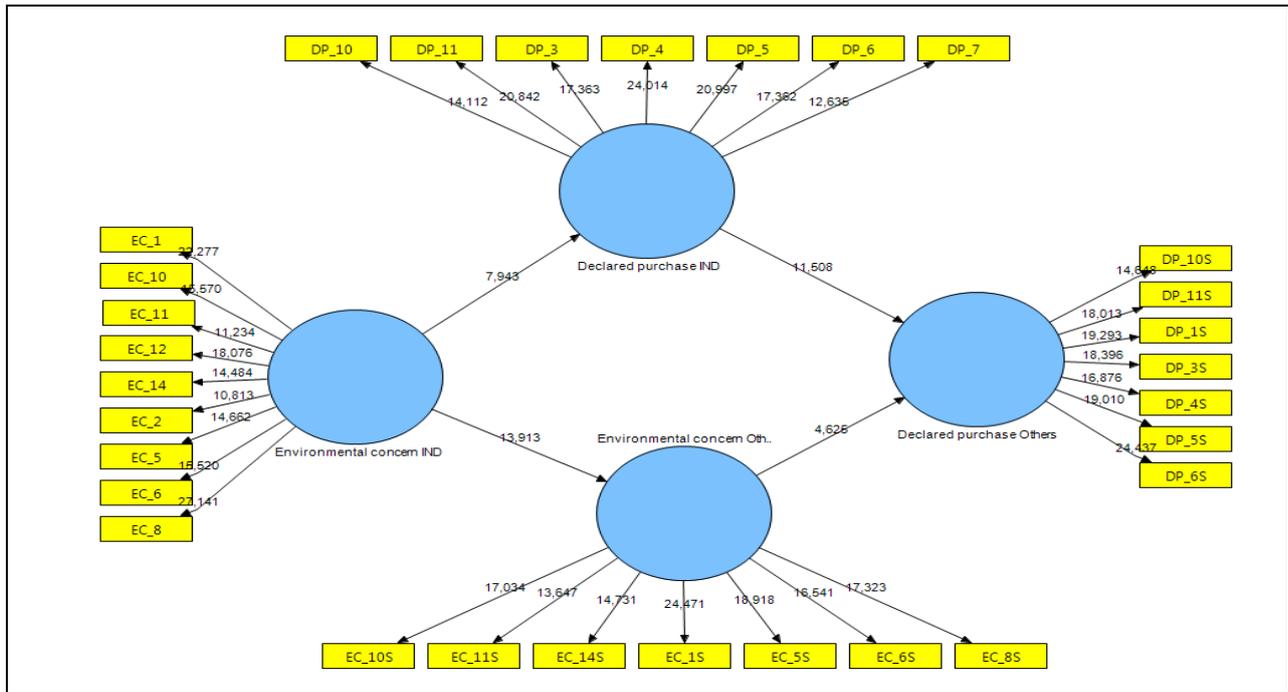


Figure 14 - SEM with the values of the Student t tests obtained via the Bootstrapping module of the SmartPLS

The Stone-Geisser Indicator (Q^2) evaluates how much the model approaches what was expected of it (or the model prediction quality or accuracy of the adjusted model). As criteria of the evaluation, values greater than zero should be obtained (HAIR et al., 2014). A perfect model would have $Q^2 = 1$ (shows that the model reflects reality – without errors).

The Cohen’s Indicator (f^2) is obtained by the inclusion and exclusion of model constructs (one by one). Just how useful each construct is for the adjustment model is evaluated. Values of 0.02, 0.15 and 0.35 are considered small, medium, and large

respectively (HAIR et al., 2014). Also, the f^2 is evaluated by the ratio between the part explained and the part not-explained ($f^2 = R^2 / (1 - R^2)$).

Both are obtained by using the Blindfolding module on the SmartPLS (see figure 8). The values of Q^2 are obtained by reading the general redundancy of the model and f^2 by reading the commonalities (see figure 7).

The interpretation of table 7 shows that the values of Q^2 , as well as those of f^2 , indicate that the model is accurate and that the constructs are important for the general adjustment of the model.

Table 7 - Values of the indicators of the predictive validity (Q^2) r Stone-Geisser indicator and the Effect size (f^2) or Cohen’s indicator.

VL	CV RED (Q^2)	CV COM (f^2)
Declared purchase IND	0.076487	0.388054
Declared purchase Others	0.310113	0.361844
Environmental concern IND	0.379131	0.379131
Environmental concern Others	0.201841	0.352414
Valores referenciais	$Q^2 > 0$	0.02, 0.15 e 0.35 are considered small, medium and large

Lastly, one should also evaluate the general adjustment indicator of the model. In this sense, for the models in which all of the constructs are reflexive, Tenenhaus et al. (2005) proposed a Goodness of Fit (GoF) which is basically the geometric mean (square root of the product of two indicators) between the median R^2 (goodness of fit of the structural model) and the mean weighted of the AVE (goodness of fit for the measuring model). Wetzels et al. (2009) suggest that the value 0.36 is adequate, for the areas of the social and behavioral sciences. Thus, doing this calculation with that value, we obtained 0.4492, indicating that the model had an adequate adjustment.

Once the evaluation of the adjustment quality has been finished, we present the interpretation of the

path coefficients (see table 8). These are interpreted such that the betas (β) of the simple or ordinary linear regressions, that is, for example, between the constructs or LVs Environmental concern Others \rightarrow Declared purchase Others the value of the path coefficient is 0.288. This means that increasing the exogenous LV Environmental concern Others by 1, the endogenous Declared purchase Others, increases by 0.288. Further detail about interpretation can be obtained in Braga Junior et al. (2014). What calls our attention in the article indicated is that the values are different, because here we used only a part of the database to allow for other adjustments and didactically show other procedures.

Table 8 - Values of the path coefficients (Γ) of the adjusted model.

Causal Relations	Path Coefficients (Γ)
Declared purchase IND \rightarrow Declared purchase Others	0.642
Environmental concern IND \rightarrow Declared purchase IND	0.385
Environmental concern IND \rightarrow Environmental concern Others	0.6417
Environmental concern Others \rightarrow Declared purchase Others	0.288

5 CONCLUSIONS

This article does not exactly have conclusions because it is a didactic attempt to present methodological procedures of the structured equation

model by measuring the partial least square (PLS) with the software SmartPLS 2.0. Therefore, this ending will summarize the procedures for quick consultation. In this sense, we present figure 15 and Graph 1.

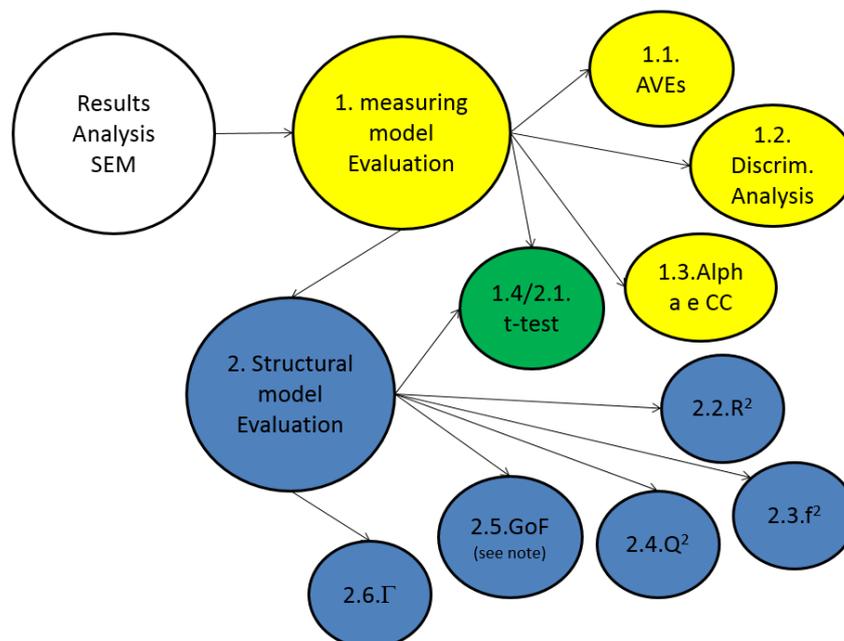


Figure 15 - Representation of the adjustment procedures of the SEM in the SmartPLS

INDICATOR/ PROCEDURE	PURPOSE	REFERENTIAL VALUES / CRITERIA	REFERENCES
1.1. AVE	Convergent Validities	AVE > 0.50	(HENSELER; RINGLE and SINKOVICS (2009)
1.2. Crossed loads	Discriminating Validity	Load values greater than the original LVs than in others	CHIN, 1998
1.2. Criteria of Fornell and Larcker	Discriminating Validity	Compare the square roots of the AVE values of each construct with the correlations (of Pearson) between the constructs (of latent variables). The square roots of the AVEs should be greater than the correlations of the constructs.	FORNELL and LARCKER (1981)
1.3. Alpha de Cronbach and Composite Reliability	Model Reliability	AC > 0.70 CC > 0.70	HAIR et al. (2014)
1.4. Student t Test	Evaluation of the significances of the correlations and regressions	$t \geq 1.96$	HAIR et al. (2014)
2.1. Evaluation of the coefficients of Pearson's determination (R^2):	Evaluate the portion of variances of the endogenous variables, which is explained by the structural model.	For the area of social and behavioral sciences, $R^2=2\%$ is classified with a small effect, $R^2=13\%$ as a median effect and $R^2=26\%$ as a large effect.	COHEN (1988)
2.2. Size of the effect (f^2) or Cohen's Indicator	Evaluate how much each construct is useful to the model adjustment.	Values of 0.02, 0.15 and 0.35 are considered as small, median and large.	HAIR et al. (2014)
2.4. Predictive Validity (Q^2) or Stone-Geisser indicator.	Evaluates the accuracy of the adjusted model.	$Q^2 > 0$	HAIR et al. (2014)
2.5. GoF (See note)	It is a score of the global quality of the adjusted model.	GoF > 0.36 (adequate)	TENENHAUS et al. (2005); WETZELS, M.; ODEKERKEN-SCHRÖDER, G.; OPPEN
2.6. Path Coefficient (Γ)	Evaluation of the causal relations.	Interpretation of the values to the light of the theory.	HAIR et al. (2014)

Graph 1 - Synthesis of the SEM adjustments in the SmartPLS

Note: Until recently the GoF was calculated to evaluate the model as a whole, but Henseler and Sarstedt (2012) showed that it has no power to distinguish valid models and not valid models. Thus, we suggested not use the GoF as an indicator

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