Quantitative Research
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PLS-SEM Research Design: Revising Traditional Quantitative Research Model to Structural Equation Model

Eve Thullen, Claremont Graduate University

Background

The traditional statistical methods often used by social scientists are typically called first-generation techniques *(Fornell, 1982, 1987)*. These techniques include regression-based approaches such as multiple regression, logistic regression, and analysis of variance but also techniques such as exploratory and confirmatory factor analysis, cluster analysis, and multidimensional scaling.

SEM-Structural Equation Modeling
However, for the past 20 years, many researchers have increasingly been turning to new techniques to overcome the weaknesses of the old methods. These methods, referred to as structural equation modeling (SEM), enable researchers to incorporate unobservable variables measured indirectly by indicator variables. They also facilitate accounting for measurement error in observed variables *(Chin, 1998*).

When to using SEM?
Researchers would consider using Structural Equation Modeling the following five elements: (1) composite variables, (2) measurement, (3) measurement scales, (4) coding, and (5) data distributions.

PLS Path Model:
Path or relation models are diagrams used to visually display the hypotheses and variable relationships that are examined when SEM is applied. A PLS path model consists of two elements. First, there is a structural model, also called the inner model in the context of PLS-SEM that represents the constructs. The structural model displays the relationships (paths) between the constructs. Second, there are the measurement models, also referred to as the outer models in PLS-SEM, of the constructs that display the relationships between the constructs and the indicator variables.

Case 1:

This case based on the paper *"If they Trust our E-commerce Site, Will They Trust our Social Commerce Site Too? " Bansal&Chen, 2011*

This paper has an acceptable structure as a conference paper, which included research questions, methodology, data analysis, discussion, etc., however, the paper need major improvement on research methodology:

Structural Model

The structural model the author provided about the relationship between website, privacy, security concern, and Trust is not very clear. In the paper, the author listed four dimensions of Privacy that was not in the structural model. What's more, in the paper, the author demonstrated that website, reputation, and one's trust propensity could impact the level of trust in a website, yet, these factors was not in the structural model, either.

Research Methodology and Data Analysis used in the original paper:

- EFA - Exploratory factor analysis (EFA) is generally used to discover the factor structure of a measure and to examine its internal reliability. EFA is often recommended when researchers have no hypotheses about the nature of the underlying factor structure of their measure. Much like cluster analysis involves grouping similar cases, factor analysis involves grouping similar variables into dimensions. This process is used to identify latent variables or constructs. The purpose of factor analysis is to reduce many individual items into a fewer number of dimensions. Factor analysis can be used to simplify data, such as reducing the number of variables in regression models.
- ANOVA- The one-way analysis of variance (ANOVA) is used to determine whether there are any statistically significant differences between the means of three or more independent (unrelated) groups. In this research, we have more than one independent variable. Running ANOVA can be really complicated and may cause confusing.

The relationship of these factors are complicated, thus, I would recommend use PLS-SEM research methodology to estimate the complex relationships among variables in a model, such as a path model, including unobservable variable.

Revised Research Methodology and Model:

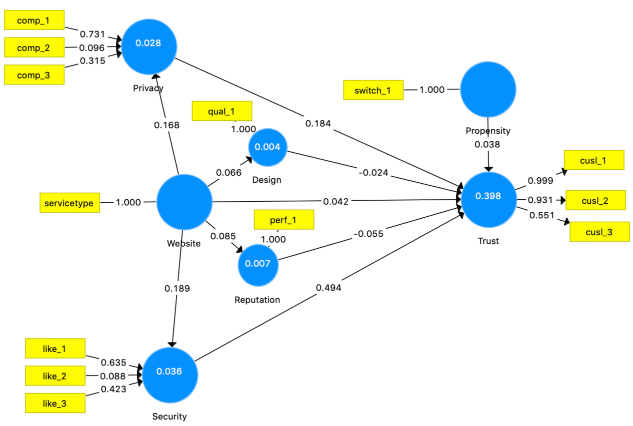
1. Revised Structural Model

- Original Model: In the paper, the author developed the theoretical model with 3 propositions: type of website, trust, and Privacy/Security Concern;
- Adjusted New Model, will separate Privacy and Security Concern; also, the author mentioned that website, reputation, and one's trust propensity could impact the level of trust. Thus we will add all these factors to the new structural model.

2. Specifying the Measurements/Indicators.

Since the constructs are not directly observed, we need to specify a measurement model for each construct. There are two type of measurements: reflective and formative measurement.
A reflective measure dictates that all indicator items are caused by the same construct;
A formative measurement based on the assumption that causal indicators form the construct by means of linear combinations.

Based on the dimension from the paper, the privacy identified four dimensions of privacy concern namely: (a) collection, (b) unauthorized secondary use, (c) unauthorized access, and (d) errors. And there are four dimensions as Security Concern: Authentication, Confidentiality, Integrity, and Non-repudiation. Indicators as following:



- Privacy Concerns (Formative):
    - PC_1: Collection
    - PC_2: Secondary Use
    - PC_3: Improper Access
    - PC_4: Errors

- Security Concerns (Formative):
  - SC_1: Authentication
  - SC_2: Confidentiality
  - SC_3: Integrity
  - SC4: Non-repudiation

To evaluate S-Commerce and Ecommerce, we will add the Type as indicator for Web. And the other constructs, WebDesign, Reputation, and Propensity will be the same as Privacy and Security, could design multiple indicators.

3. Revised Research Questions

- H-1: Users trust e-commerce sites more than s-commerce sites.
- H- 2: Security concern (SC) moderates the trust in a website such that (i) the higher concern would lead to lower trust, (ii) more so for an s-commerce site than an e-commerce site.
- H- 3: Privacy concern (SC) moderates the trust in a website such that (i) the higher concern would lead to lower trust, (ii) more so for an s-commerce site than an e-commerce site.

4. Data Collection and Sampling

In our case, we will use survey to collect our data. When empirical data are collected using survey, typically data collection issues can be happened, including missing data, suspicious response patterns (straight lining or inconsistent answers), outliers, and data distribution.

- Missing data, there are three options to deal with missing data in SmartPLS: 1) mean value replacement, the missing values of an indicator variable are replaced with the mean of valid values of that indicator. 2) casewise deletion/listwise deletion, remove all cases from the analysis that include missing values in any of the indicators used in the model. 3) pairwise deletion, uses all observations with complete responses in the calculation of the model parameters. In our case, we will use mean value replacement.
- Suspicious and inconsistent response patterns typically justify removing a response from the data set.
- Outliers should be identified, could deleted or corrected; if retained, the test result need be carefully evaluated. To run outlier diagnostics, we run a series of box plots using IBM SPSS Statistics
- Lack of normality in variable distributions can distort the result. Skewness assesses the extent to which a variable's distribution is symmetrical; Kurtosis is a measure of whether the distribution is too peaked. Absolute skewness or kurtosis values of greater than 1 are indicative of abnormal data.

5. Research Tools and Apply Model to PLS

- The SmartPLS 3 software is used to execute all the PLS-SEM analyses in this project. PLS-SEM is an OLS regression-based estimation technique that determines its statistical properties.
- The Dataset format for PLS will be a Data Matrix.
- The minimum sample size for PLS path model estimation should at least meet the 10 times rule

6. Data Analysis and Research Result

After the estimation of the model, SmartPLS opens the results report, which at the bottom of the results report, for example, the results of PLS Algorithm tables divided into four categories: Final Results, Quality Criteria, Interim Results, and Base Data.

We will begin the evaluation process by assessing the quality of reflective and formative measurement models. Assessment of reflective and formative measurement models provides evidence of the measures' quality. If the measurement characteristics of constructs are acceptable, continue with the assessment of the structural model results. The structural model estimates are evaluated to test the model's ability to predict the variance in the dependent variables. Model assessment in PLS primarily builds on nonparametric evaluation criteria based on bootstrapping and blindfolding. The evaluation of the quality of the PLS-SEM measurement and structural models criterion as following:

Formative Measurements:

1) The first step to assess the formative measurement model's convergent validity. We use redundancy analysis process, which examining its correlation with an alternative measure of the construct, using a global single item. The correlation between the constructs should be 0.70 or higher.

-- Convergent Validity/ Redundancy Analysis Assessment (PLS Report: each constructs with global indicator)

- $R > 0.708$
- $R^2 > 0.5$

2) The second step to assess Collinearity issues. A related measure of collinearity is the variance inflation factor (VIF), defined as the reciprocal of the tolerance. Each indicator's VIF value should be lower than 5; otherwise, consider eliminating indicators or merging into a single index.

-- Collinearity between Indicators (PLS Report: Collinearity Statics VIF- Outer VIF Values)

- Out VIF Values < 5

3) The third step to examine each indicator's out weight (relative importance to the construct) and outer loading (absolute importance to the construct), and use bootstrapping to assess their significance. In our case, the significance level set to 0.05. When an indicator's outer weight is nonsignificant but its outer loading is high (i.e., above 0.50), the indicator would generally be retained.

-- Significance and relevance of Out Weights
(Bootstrapping: Outer Weights)

- p value < 0.05
- T value > 1.96
- If p is not significance: check Outer Loading
  Outer Loading > 0.5, then retained the indicator
  Outer Loading < 0.5, then remove the indicator

Reflective Measurements:

1) The first criterion to be evaluated is typically Internal Consistency Reliability. The traditional criterion for internal consistency is Cronbach's alpha, which provides an estimate of the reliability based on the inter-correlations of the observed indicator variables. Also, as Composite Reliability, which measure of reliability takes into account the different outer loadings of the indicator variables.

-- Internal Consistency Reliability (PLS Report: Construct Reliability and Validity)

- Cronbach's alpha: 0.7 ~ 0.9
- Composite reliability: 0.7 ~0.9

2) The second criterion is Convergent Validity. High outer loadings on a construct indicate the associated indicators have much in common, which is captured by the construct. The size of the outer loading is also commonly called indicator reliability. A common measure to establish convergent validity on the construct level is the average variance extracted (AVE). This criterion is defined as the grand mean value of the squared loadings of the indicators associated with the construct, which is equivalent to the communality of a construct.

-- Convergent Validity, outer loading, indicator reliability (PLS Report: Outer Loading)

- Outer Loadings > 0.708, (if outer loading < 0.708, remove the indicator)
- Indicator Reliability > 0.5 = $(0.708)^2$
- AVE >= 0.5

3) The third criterion is Discriminant validity, which the extent to which a construct is truly distinct from other constructs by empirical standards. We can approach by Cross-Loading analysis and Fornell-Larcker criterion. In our case, we use heterotrait-monotrait ratio (HTMT) of the correlations. HTMT is the mean of all correlations of indicators across constructs measuring different constructs relative to the mean of the average correlations of indicators measuring the same construct. The criterion as following:

-- Discriminant Validity (PLS Report: Discriminant Validity, HTMT)

- Discriminant < 0.85

Assessing Structural Model:

Step 1 Assess structural model for Collinearity Issues. we apply the same measures as in the evaluation of formative measurement models. we consider tolerance values below 0.20 (VIF value above 5) in the predictor constructs as critical levels of collinearity.

--- Collinearity: (PLS: Collinearity Statics VIF- Inner VIF Values)

- Inner VIF Values < 5

Step 2 Assess the significance and relevance of the structural model **Path Coefficients.** We use Bootstrapping to assess the significance of path coefficients. Commonly used critical values for two-tailed tests are 1.65 (significance=0.1), 1.96 (significance=0.05), and 2.57 (significance level=0.01). In our case, we use 0.05.

For indirect effects and total effect. We also could find the total effect and indirect effect result from PLS report

-- Significance and relevance of Path Coefficients, Bootstrapping Test
(Bootstrapping: Path Coefficients, total effect, and indirect effect)

- p value < 0.05
- T value > 1.96

Step 3 Assess Coefficient of Determination R^2. This coefficient is a measure of the model's predictive power and is calculated as the squared correlation between a specific endogenous construct's actual and predicted values. The adjusted R^2 be modified according to the number of exogenous constructs relative to the sample size.

Step 4, Assess the effect size f^2. It allows assessing an exogenous construct's contribution to an endogenous latent variable's R^2 value. The value estimated as (0.02, small), (0.15 medium), (0.35 large).

-- Coefficient of Determination and effect size (PLS Report: R Square, f Square)

- $R^2 > 0.5$
- $f^2 > 0.02$

Step 5, Asses the predictive relevance Q^2. Q^2 measures the model's out-of-sample predictive power. The Q^2 value is obtained by using the blindfolding procedure for a specified omission distance D. Dvalues between 5 and 10.

Step 6, Assess the effect size q^2. It allows assessing an exogenous construct's contribution to an endogenous latent variable's Q^2 value. The value estimated as (0.02, small), (0.15 medium), (0.35 large).

-- Predictive Relevance and effect size, Blindfolding Test
(Blindfolding Report: Q Square)

- $Q^2 > 0.5$
- $q^2 > 0.02$, (q calculated from Q)

Case 2:

This case based on the paper "Exploring the Influence of Trust in the Development of Transactive Memory Systems in Virtual Project Teams" Leoz&Khazanchi, 2015 *Association for Information Systems*

Research Questions:

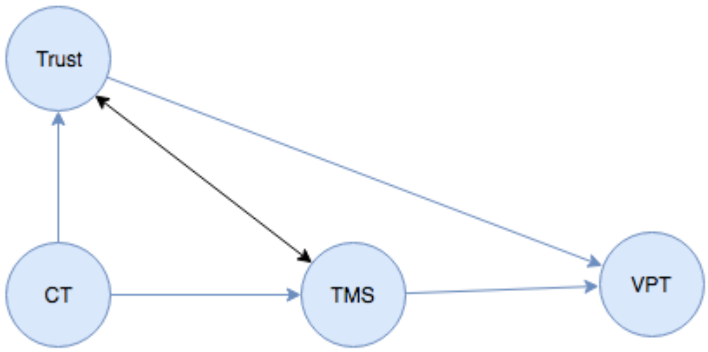
1. How does trust influence the development of TMS and performance of virtual project teams
2. How does the use of collaboration technologies affect the development of trust within virtual project teams?

Research Design:

Stage 1: Specifying the Structural Model

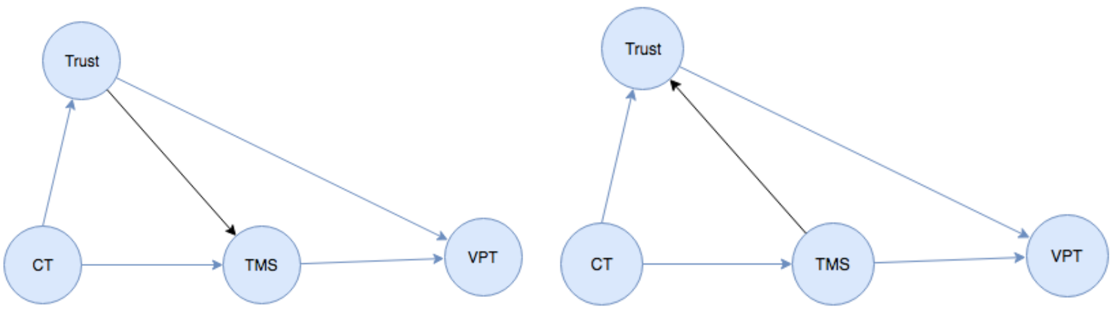
- Original Structural Model

In the paper, the author developed a theoretical model with 6 propositions that explained the relationship between Role of Trust on TMS Development and VPT Performance, and the relationship between the use of information technology on the Trust and TMS.



Original Cyclic Model

- Adjusted Structural Model /Simplified Model
  From the original model, the relationship between Trust and TMS is cyclic. To simplified the model to acyclic, we can test the propositions 3 and 4 separately:



Model A Model B

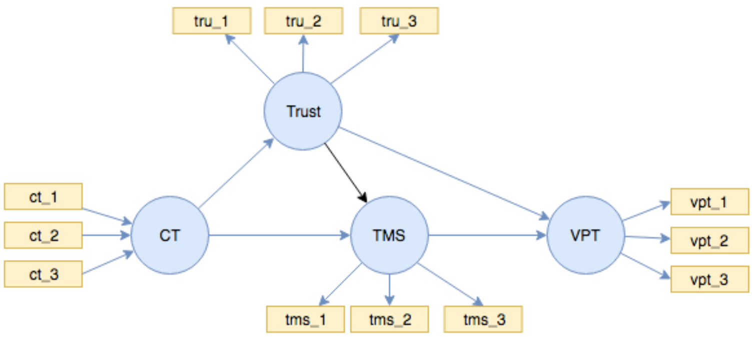
Model A: In virtual project teams, higher levels of trust will lead to more developed transactive memory systems.

Model B: In virtual project teams, more developed transactive memory systems will lead to higher levels of trust among team members.

Stage 2: Specifying the Measurements/Indicators
Since the constructs are not directly observed, we need to specify a measurement model for each construct. There are two type of measurements: reflective and formative measurement.
A reflective measure dictates that all indicator items are caused by the same construct;
A formative measurement based on the assumption that causal indicators form the construct by means of linear combinations.

For Model A, higher levels of trust will lead to more developed transactive memory systems. Based on the paper, indicators of the Constructs Model A designed as following:

1. Collaboration Technologies(Formative)
    ct_1: Ease of use of technologies
    ct_2: Flexibility of dispersion
    ct_3: Information Transaction
2. Trust(Reflective)
    tru_1: Cohesion
    tru_2: Commitment
    tru_3: Satisfaction
3. TMS (Reflective)
    tms_1: Knowledgeable
    tms_2: Specialization
    tms_3: Knowledge Exchange
4. VPT Performance(Reflective)
    vpt_1: Efficient
    vpt_2: Effective
    vpt_3: Completion



Structural Model A with Indicators

For Model B, what we can do is change the direction between Trust and TMS, to evaluate how transactive memory systems impact the trust among team members.

Stage 3: Data Collection and Examination
In our case, we will use survey to collect our data. When empirical data are collected using survey, typically data collection issues can be happened, including missing data, suspicious response patterns (straight lining or inconsistent answers), outliers, and data distribution.

- Missing data, there are three options to deal with missing data in SmartPLS: 1) mean value replacement, the missing values of an indicator variable are replaced with the mean of valid values of that indicator. 2) casewise deletion/listwise deletion, remove all cases from the analysis that include missing values in any of the indicators used in the model. 3) pairwise deletion, uses all observations with complete responses in the calculation of the model parameters.
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- Lack of normality in variable distributions can distort the result. Skewness assesses the extent to which a variable's distribution is symmetrical; Kurtosis is a measure of whether the distribution is too peaked. Absolute skewness or kurtosis values of greater than 1 are indicative of abnormal data.

Stage 4: Apply Dataset and Model to PLS
- The SmartPLS 3 software is used to execute all the PLS-SEM analyses in this project. PLS-SEM is an OLS regression-based estimation technique that determines its statistical properties.

- The Dataset format for PLS will be a Data Matrix.
- The minimum sample size for PLS path model estimation should at least meet the 10 times rule
- PLS Settings, the algorithmic options and parameter settings:
  - Weighting Schemes: path weighting approach been set. This weighting scheme provides the highest R^2 value for endogenous latent variables
  - Maximum Iterations: 300, the selection of a maximum number of 300 iterations should ensure that convergence is obtained at the stop criterion of 1 · 10–7.
  - Stop Criterion: A threshold value of 1 · 10–7 been set, ensures that the PLS-SEM algorithm converges at reasonably low levels of iterative changes in the latent variable scores.
  - Initial Value: initialization values of +1 are specified for all relationships in the measurement model during the first iteration.
  - Missing Value: Mean Replacement been set.
  - Weighting Vector: assigns each observation a different importance in the PLS-SEM estimation based on some criterion.

Research Results: after the estimation of the model, SmartPLS opens the results report, which is the same as case study 1.The evaluation of the quality of the PLS-SEM measurement and structural models criterion as following: Reflective Measurements; Formative Measurements; Assessing Structural Model.