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Comparing PLS-SEM and SEM Bayesian for Small Sample in TAM Analysis

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Abstract

Technology Acceptance Model (TAM) employed statistics method to validate the relation between constructs in the model. SEM is the most often statistics method that used in TAM analysis. Small sample is crucial problem in Structural Equation Modelling (SEM). SEM with Bayesian approach and SEM-PLS are the alternatives solution for small sample problem in SEM. The main differentiation between SEM-PLS and SEM Bayesian is how to develop resampling for small samples. This study will compare SEM with Bayesian approach and SEM-PLS in TAM analysis.

Keywords: TAM;SEM-PLS; SEM Bayesian

1. Introduction

Technology Acceptance Model (TAM) needs statistics method to validate the relations between constructs in TAM's model. SEM also explains how a construct will influence another constructs in a model. Structural Equation Modelling (SEM) is the most often method that employed in TAM analysis. Anggorowati et. al (2012) explained 64% TAM research make use of SEM and 15% employed SEM-PLS. SEM needs some assumptions to estimate the parameters. Some assumptions of SEM are normality and linearity. There are some solutions for small sample size in SEM analysis. Sample size plays important rule in order to fill normality assumption. Sample size has to be agree with the number

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of parameters in a model. Parameters in a model with insufficient sample will not be identified and the model is not valid.

SEM-PLS was known as an alternative of small sample size . SEM-PLS methodology has gained prominent recognition in research settings such as management information systems (e.g., Dibbern, Goles, Hirschheim, & Jayatilaka,2004), e-business (e.g., Pavlou & Chai, 2002), organizational behavior (e.g., Higgins, Duxbury, & Irving, 1992), marketing (e.g., Reinartz, Krafft, & Hoyer, 2004). SEM-PLS is an alternative to handling small sample size. Bayesian already known as a modern statistics method. It employee computational statistics to enhance the process of free assumptions estimation.

It is important to involve many statistics method to analyze technology adoption model. The study to find the fix method to the data is an important part of analysis process. This paper will compare two statistics methods for TAM analysis in order to handling small sample size.

2. SEM-PLS and SEM Bayesian Overview

2.1. SEM-PLS

SEM-PLS is an another approach of SEM. In many literatures SEM is equivalent with covariance based SEM (CB-SEM). PLS-SEM has some differences with CB-SEM . Hair et.al (2011) explain that PLS-SEM is causal modeling in which to maximizing the explained variance of dependent latent construct. PLS-SEM has been increasingly specially for marketing and many business research (Henseler, Ringle and Sinkovics, 2009). Many researcher explained that PLS –SM is less strict and less right for purpose the examining relations between latent variables. In spite of the fact that many researchers viewed that PLS-SEM is “silver bullet” for dealing with small sample size (Hair et al, 2011). Many researchers also explained that PLS-SEM minimize the residual variance of the endogenous constructs. Even though PLS-SEM can be applied in many cases, it is important to be concerned about the interpretation of the result. One of the differences of PLS-SEM is that it estimate loading factor based on their prediction of the endogenous construct and not their shared variance among indicator variables in the same construct. Another reasons to be concern are that PLS-SEM focus on maximizing partial model structures and another problem is that it no adequate global measure of goodness of fit.

PLS-SEM has two steps process estimation. First process is assess measure’s validity and reliability, the second process is examine the structural relations. The evaluation criteria for the structural model are R^2 and the level significance of the path coefficients (Hair et al, 2011). For the reason that PLS-SEM explained that latent variable’s variance , thus the R^2 construct’s level should be high. In PLS structural model, the level of R^2 be certain of the field research or study. Hair et. Al (2011 explained that R^2 is high for a research of consumer study, and in marketing research , the values of 0.75, 0.50 and 0.25 for endogenous latent variables as a decree of criteria, substantial, moderate or weak.

The path coefficient of PLS model take to mean as beta coefficient in least square regression. Bootstrapping procedure will calculate of each path coefficient .The capability to predict of the model will measure by predominant’s measure of predictive relevance The Stone-Geisser’s Q^2. It assume that the model must be able to adequate predict each endogenous latent’s constructs indicators. In PLS- SEM the Q^2 will be evaluated by blindfolding procedures. The suggestion is if the value of Q^2 more than zero, it can be claimed that the explanatory of latent constructs exhibit predictive relevance.

PLS-SEM is free from the assumption of normality distribution. The aftermath is that PLS-SEM has to put on nonparametric bootstrapping (Davidson & Hinkley, 1997; Efron & Tibshirani, 1993). Bootstraping procedure take in repeated random sampling that replace the original sample to obtain a bootstrap sample and standard error for hypothesis testing. Henseler, Ringle and Sinkovics (2009) viewed that bootstrap samples allow the estimated coefficients in PLS-SEM. The bootstrapped parameters are employed to create an empirical sampling distribution for each parameter of the model, and the standard deviation is used to obtain the standard error of paramters.

2.2. SEM Bayesian

Another method which is free distribution assumption is SEM with Bayesian approach. SEM Bayesian is developed by Lee (2007). The same as PLS-SEM, SEM Bayesian needs computational method in order to obtain the estimation. Different with PLS-SEM with sample variance matrix analysis, the Bayesian method analysis is based on raw individual random observations. It has several advantages, first, the development statistical methods is based on the first moment properties of the raw individual observations. Second it leads to direct estimation of the latent variables which better than classical regression. Third it gives more direct interpretation and can utilize the common technique in regression such us outlier and residual analysis (Lee, 2007). According to Little (2003), Anggorowati et. al (2012) explained that in inference perspective the attractive of Bayesian approach consist of : a) provide a unified framework of all problems of survey inference such as analytical estimate, small or large sample inference, ignorable sample selection methods and problems where modelling assumption play more central role such as missing data or measurements error, b) many standards design-based inference can be derive from Bayesian approach, c) allows the prior information about a problem to be incorporate in the analysis in simple and clear way, d) deals with nuisance parameter in a natural and appealing way, e) satisfied the likelihood principle, f) with modern computational tools make Bayesian analysis much more practically feasible than in the past.

SEM Bayesian is lay on Bayesian rule. Bayesian rule can be expressed with

$$\log p(\theta|Y, M) \quad \alpha \quad \log p(Y|\theta, M) + \log p(\theta) \qquad (1)$$

According to Bayesian rule, SEM-PLS needs to select the prior distribution. It can be refer to prior distribution was based on previous research by Lee (2007). There are two hierarchy of prior distribution. First, is corresponding to a measurement equation:

$y_i = \Lambda\omega_i + \varepsilon_i$

Where ω_i is distributed as $N(0, \Phi)$ and ε_i is distributed as $N(0, \Psi_\varepsilon)$. Let Λ_k^T be kth row of Λ, a conjugate type prior distribution of Λ_k, ψ_{ek} will be ψ_{ek}^{-1} D Gamma [$\alpha_{0ek}, \beta_{0ek}$] and for $(\Lambda_k|\psi_{ek})$ is $(\Lambda_k|\psi_{ek})$ D $N(\Lambda_{0k}, \psi_{ek} H_{0yk})$, where $\alpha_{0ek}, \beta_{0ek}$ and elements in Λ_{0k}, H_{0yk} are hyper parameters and H_{0yk} is a positive definite matrix. The conjugate prior of Φ is Φ^{-1} D $W_q(R_0, \rho_0)$ and $\alpha = \alpha$ D $N(0, I)$, $\Lambda_k = \Lambda_k$ D $N(\Lambda_{0k}, \psi_{ek} I)$, and $\Gamma = \Gamma$ D $N(\Gamma_0, \psi_\delta I)$, where I is identify matrices.

The posterior distribution $(\theta|Y)$ could be obtained via integration. Unfortunately most of the integrations does not have a closed form. Lee (2007) employed the idea of data augmentation which proposed by Taner and Wong (1987). The idea of data augmentation is treat the latent quantities as hypothetical missing data and then augment the observed data with latent quantities so the posterior distribution will easily to analyse base on complete data set.

The concept of data augmentation was influenced by latent variables. For complex posterior density $p(\theta|y)$, Bayesian analysis was performed with $p(\theta, \Omega|Y)$, where Ω is asset of latent variables of model. With complete data set (Ω, Y), the conditional distribution which is involved in posterior analysis is $p(\Omega|\theta, Y)$. MCMC was implemeted to simulate the obervation of $p(\theta, \Omega|Y)$ and built the iterations for describe the probability density function of $p(\theta, \Omega|Y)$ and $p(\Omega|\theta, Y)$.

3. Data and Model Structure

Corresponding to Anggorowati et. al (2012) The case study in this research is TAM for technology adoption in government institution. The characteristics of government institution in order to technology adoption are, first the process is mandatory. The users has to follow the policy to which the technology will be used. They have to use it to increase their job. Although the process is mandatory, user acceptance of the technology can be measured. The second characteristic is organizational interventions will be influence the user acceptance. Figure 1 showed the structure of TAM model.

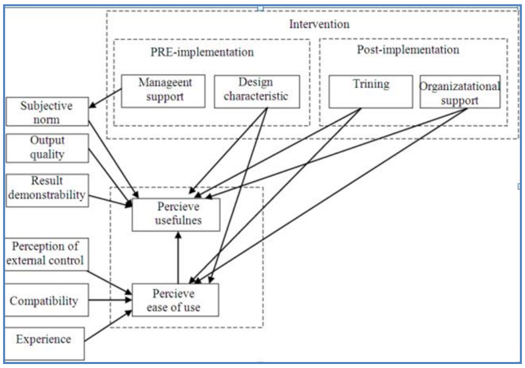

Fig. 1 TAM structure

The TAM structure consists of 12 constructs. The constructs that describe the organizational interventions are management support, design characteristics, training and organizational support. Subjective norm, output quality, result demonstrability, perception of external control, compatibility and experience, perceived usefulness and perceived ease of use are individual perspectives.

The number of respondents is 34, it shows the real problem that TAM model can be in small sample data. Refer to figure 1, the model has 9 exogenous variables and 3 endogenous variables. Figure 2 denotes the SEM structure of TAM and parameters to be estimated . The constructs are subjective norm (SN), output quality (OQ), result demonstrability (RD), perception external control (PEC), compatibility (COM), Experience (EXP), management support (MS), design characteristics (DC), training (TR), organizational support (OS), perceived ease of use (PEU, and perceived of usefulness (PU).

4. Analysis

4.1. SEM-Bayesian

The estimation of SEM Bayesian was done via Win Bugs. The estimation was done in 10000 iteration. Figure 2 shows the result of SEM-Bayesian analysis. It obtained estimate parameters γ, β, ψ, ϕ. The range of λ is 0.737-1.11. The result gives 2 coefficient $\beta_1 = 0.7$ (subjective norm and perceived of usefulness) and $\beta_2 = 0.6$ for perceived ease of use to perceived of usefulness. The range of γ is between -0.67 to 0.62. The significant relations between latent variables are : management support to subjective norm, subjective norm to perceive of usefulness, perception of external control to perceived ease of use.

There are eleven relations between latent variables are not significant. They are: perceived ease of use to perceived of usefulness, output quality to perceived of usefulness, result demonstrability to perceived of usefulness, compatibility to perceived ease of use, experience to perceived ease of use, training to perceived ease of use, training to perceived of usefulness, design characteristic to perceived ease of use, design characteristic to perceived of usefulness, organizational support to perceived ease of use, and organizational support to perceived usefulness. The residual analysis was performed to identify the goodness of the models. The mean of residual of model are near to 0.

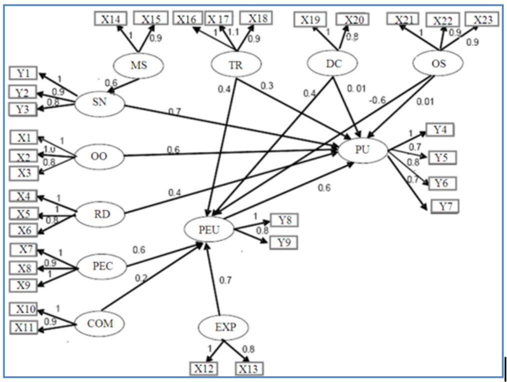

Fig. 2 SEM Bayesian estimation

4.2. SEM-PLS

SEM-PLS estimation was conducted by SmartPLS software. It was involved two step process of estimation. The first process is inner model and the second process is outer model. Inner model represent the structural model and outer model represents the measurements model. Bootstrapping was done in 5000 iteration, the estimation could not be done in 10.000 iteration.

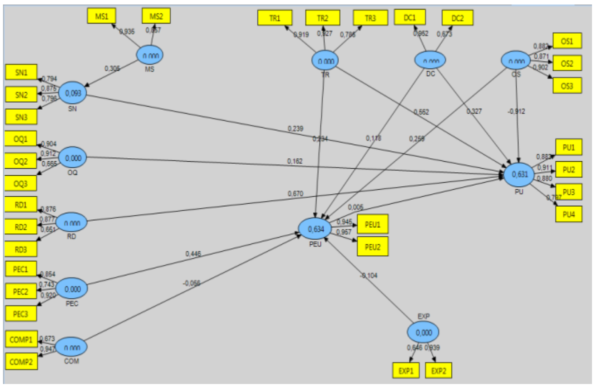

Fig. 3 SEM –PLS estimation

The SmartPLS obtained $\beta_1 = 0.239$ and $\beta_2 = 0.005$. the range of γ parameter is -0.912 to 0.670. the t-values showed that 5 path coefficients are significant, there are management support to subjective norm, organizational support to perceived usefulness, perception of external control to perceived ease of use, result demonstrability to perceived usefulness, and training to perceived of usefulness. The others path coefficients are not significant. The value of R^2 show that relation perceived ease of use with other exogenous variable is strong with value of $R^2 = 0.67$, and the relation of perceived ease of use with other variables is strong with value of $R^2 = 0.63$. The relation between subjective norm and management support is weak with value of $R^2 = 0.09$.

5. Discussion

SEM-PLS and SEM Bayesian have different steps of estimation. The main process of estimation for small sample is resampling of the data. SEM-PLS made for 5000 iteration and it did not work for 10.000 iteration. The resampling for SEM-Bayesian was made in 10.000 iteration, and obtained bigger value of β and γ parameter. Path coefficient is also different, SEM-PLS has five significant coefficients and SEM Bayesian has three significant coefficients.

SEM Bayesian and SEM-PLS are different methods to handle small sample in SEM estimation. The result shows that SEM Bayesian obtained three coefficient that are significant and eleven path coefficient that are not significant. In the other side SEM-PLS can obtained five coefficient that are significant and nine coefficient that are not significant. Mercaulides et al. (1996) explained that different coefficient estimate from each approach did not show the difference of the methods. Based on Mathes (1993) and McDonald (1996) Marcaulides et al. also clarify that “laten” PLS variables are not true latent variables as they define in SEM since they were not derive to explained the covariant of their indicator. In other words they can not be found as weighted sums of the manifest variables.

6. Conclusion

There are some differences between SEM-Bayesian and SEM-PLS estimation. Both of them did the estimation in linear model. It is has to be clear about the linearity of the data. Even though the two approaches obtained the path coefficients and loading from each indicators, the basic concepts of SEM could not be found equally in SEM-PLS and SEM –Bayesian. SEM Bayesian estimate direct to the raw data, and on the contrary SEM-PLS estimate base on the variance matrix, it does not describe the true latent variables.

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