

PARTIAL LEAST SQUARES: ANOTHER METHOD OF STRUCTURAL EQUATION MODELING ANALYSIS

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ABSTRACT

Structural Equation Modeling (SEM) adalah salah satu cara analisis data multivariat yang populer di kalangan peneliti di bidang bisnis, seperti akuntansi dan sistem informasi. Para peneliti sebelumnya telah mengenal SEM berbasis kovarian seperti yang digunakan dalam LISREL dan AMOS. Sebenarnya masih ada lagi jenis SEM yaitu yang dikenal sebagai Partial Least Squares (PLS). Jenis ini menawarkan alternatif terhadap SEM berbasis kovarian yang persyaratan penggunaannya cenderung lebih banyak dan rumit. Paper ini bertujuan untuk memberikan pemahaman mengenai Partial Least Squares. Berbagai aspek PLS seperti manfaat, keterbatasan, persyaratan penggunaan termasuk prosedur evaluasi modelnya juga dibahas.

Keywords: *Structural Equation Modeling (SEM), LISREL, Partial Least Squares (PLS), Research Methodology, Reflective and Formative Indicators*

INTRODUCTION

Structural Equation Modeling (hereafter SEM), which is one of multivariate data analysis techniques becomes popular among social science researchers. Business researchers, including from accounting, management and information technology fields seem to be advanced users of the SEM. Among the most commonly used SEM tools are LISREL and AMOS. These tools can be classified as covariance-based SEM. Despite its popularity, covariance-based SEM, theoretically, needs rigorous requirements - such as data normality, minimum number of cases and reflective indicators - which often cannot be met by researchers.

As an alternative for the covariance-based SEM, partial least squares approach that is component-based SEM can be used (Barclay, Higgins & Thompson, 1995; Chin, 1998b; Fornell & Bookstein, 1982; Lohmoller, 1988). So far, PLS approach is less known than the

covariance-based SEM due to the following reasons. Firstly, PLS is relatively new than covariance-based SEM. PLS has been developed in early 80's, among others, by Wold (1980; 1982), Fornell & Larcker (1981), and Fornell & Bookstein (1982). It is plausible if people are more familiar with LISREL or AMOS than PLS. Secondly, the PLS tool is limited. There are few PLS software available such as PLS PC and PLSGraph. Based on above mentioned reasons, this paper, therefore, aims to give an insight into various aspects of partial least squares. Having read this paper, it is expected that readers will aware that there is another SEM technique partial least squares, which is considered as complement of the currently available covariance-based SEM.

The remainder of this paper is structured as follows. Limitations and advantages of partial least squares approach are explained in the next section. Distinctions of two types of item/indicator are then illustrated. This is

followed by discussion on procedures of partial least squares analysis. After that, model evaluation, which highlights the validity issues, R-square and bootstrapping is discussed. Then, some concerns regarding PLSGraph software is provided. Finally, concluding remarks will be presented in the end of this paper.

LIMITATIONS AND ADVANTAGES OF PLS

PLS, which is a second-generation multivariate data analysis tool, needs less stringent requirements than the covariance-based SEM. The use of partial least squares is suitable in the following circumstances¹: (1) Research model indicates more than one dependent variable (endogenous variable); (2) The data is not multivariate normal; (3) Small samples or limited number of cases/usable responses², i.e. less than 200 cases; (4) Research model involves formative and/or reflective items.

Structural equation modeling assumes that the relationship between items and their constructs and relationship among constructs are linear (Gefen, Straub & Boudreau, 2000). Unlike linear regression, which enables data transformation to deal with non-linear relationship, PLS so far does not have tools to handle non linear relations (Gefen, Straub & Boudreau, 2000). Further, PLS has no established tools to overcome the issues of multicollinearity, outliers, heteroscedasticity and polynomial relationship (Gefen, Straub & Boudreau, 2000).

Despite the above mentioned limitations, one advantage of the PLS approach, among others, is its ability to map paths to many dependent variables in the same research model and to analyse all paths in structural

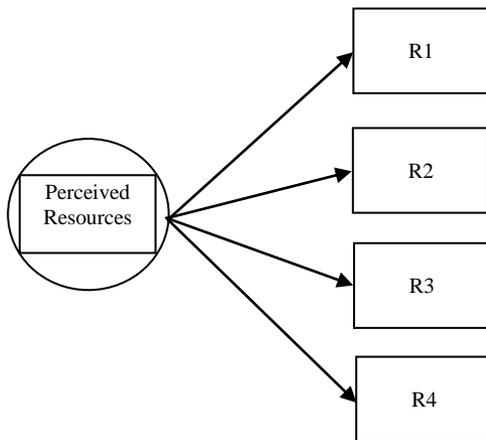
model simultaneously rather than one at a time (Fornell & Bookstein, 1982; Barclay, Higgins & Thompson, 1995; Gefen, Straub & Boudreau, 2000). Other advantage of PLS is that it needs fewer cases than a covariance-based SEM (Chin & Newsted, 1999; Gefen, Straub & Boudreau, 2000). It is argued that PLS can handle cases as small as 10 times the number of items in the most complex construct (Gefen, Straub & Boudreau, 2000). Further, such ability will enable researchers to split the data set into two groups, which may not be easy to do in covariance-based SEM. The first data set is used to test an initial model, and the second data set is used to test the revised model. In addition, PLS has a less extensive set of statistics than covariance-based SEM such as LISREL (Gefen, Straub & Boudreau, 2000). Finally, PLS is robust in regard to multivariate normality deviation because data are not assumed to be multivariate normal (Fornell & Bookstein, 1982; Chin, 1998b; Gefen, Straub & Boudreau, 2000).

REFLECTIVE AND FORMATIVE ITEMS

According to Chin (1998a), SEM analysis assumes that items/indicators used are *reflective*. This suggests that items in the respective construct/latent variable (LV) are caused by the same underlying concept. Graphically, the reflective item is shown by an arrow leading toward the items/indicators. The example of reflective items is depicted in figure 1. A change in item R4 will imply a change in items R1, R2 and R3. In addition, a change in item R1 will also lead to changes in R2, R3, and R4. The use of reflective items, therefore, implies that a change in an item will lead to a similar directional changes at other items (Chin, 1998a).

¹ To decide which technique (PLS, LISREL or Regression) is suitable for certain research, a paper by Gefen, Straub & Boudreau (2000) is worth studying.

² For further discussion regarding the use of small samples in SEM, please check Chin's & Newsted's (1999) paper.



- R1: *I have the resources, opportunities, and knowledge I would need to use a database package in my job.*
- R2: *There are no barriers to my using a database package in my job.*
- R3: *I would be able to use a database in my job if I wanted to.*
- R4: *I have access to the resources I would need to use a database package in my job.*

Figure 1 Reflective Items³

Another type of indicators is *formative* that is defined as “measures that form or cause the creation or change in a LV” (Chin, 1998a, p. ix). These items need not be correlated. In the Chin’s (1998b) words:

“Formative indicators are not assumed to be correlated nor they measure the same underlying phenomenon. Instead, formative indicators are viewed as the cause variables that provide the condition under which the LV they are connected to is formed” (p. 306).

Figure 2 shows the formative items. The arrows are pointing from items/indicators toward LV. There are three items, education, occupational prestige and residence that form individual’s socio-economic status (SES). A positive change in individual’s education can

improve his/her SES. It does not necessary, however, imply the improvement in the occupational prestige and residence. In addition, a negative change in individual’s SES caused by job losses does not necessary imply a negative change in his/her education and residence. Chin (1998a) suggests that one can check whether or not the items is formative by asking the following question. Does change in one item lead to the same directional change in other items? If the answer is not, these items in fact are formative.

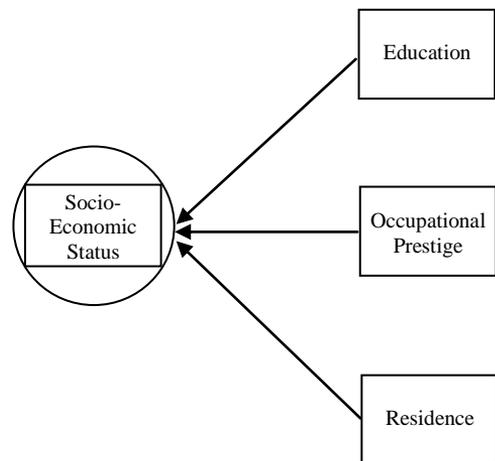


Figure 2 Formative Items⁴

The use of formative items in covariance based SEM can lead to serious problems concerning validity of the results and conclusions. Yet, this is common in psychological and sociological journals (Cohen et al., 1990). In regard to formative indicators, Chin (1998a) says,

“Because SEM technique such as LISREL attempt to account for all the covariance among its measures, the inclusion of formative measures becomes problematic. All items must be reflective to be consistent with the statistical algorithm that assumes that the correlations among

³ The example was obtained from the work of Mathieson, Peacock, & Chin (2001)

⁴ These items were obtained and extended from Chin’s (1998a) paper.

indicators for a particular LV are caused by that LV (p. ix)."

To provide answer for such problem, Chin (1998b) proposes that component-based approach known as partial least squares enables researcher to use both reflective and formative items in research model. He argues that the algorithm in PLS supports both types of items⁵.

PARTIAL LEAST SQUARES PROCEDURES

The computer software used to analyse data was PLSGraph beta version 3.0 that is developed by Prof. Wynne Chin (www.plsgraph.com). The data analysis procedure used in a Partial Least Squares analysis are described as follows:

"At the measurement model level, PLS estimates item loadings and residual covariance. At the structural level, PLS estimates path coefficients and correlations among the latent variables, together with the individual R² and AVE (Average Variance Extracted) of each of the latent constructs. T-values of both paths and loadings are then calculated using either jackknife or a bootstrap method. Good model fit is established with significant path coefficients, acceptably high R² and internal consistency (construct reliability) being above .70 for each construct" (Gefen, Straub & Boudreau, 2000, pp. 36-37).

Barclay et al. (1995) suggest that a PLS model is analysed and interpreted in two sequential steps: firstly, reliability and validity assessment of the measurement model; secondly, assessment of the structural model. Although a PLS model is analysed in measurement and structural parameters, these are estimated simultaneously (Barclay, Higgins & Thompson, 1995; Igbaria, 1993; Igbaria,

Guimaraes & Davis, 1995; Igbaria et al., 1997; Hulland, 1999; Khalifa, Limayem & Liu, 2002). Therefore, PLS analysis procedure can be undertaken with two data sets as commonly used in structural equation modelling analysis. It is also possible to use only one data set, which is helpful in the case of limited sample size.

In the interest of model validation, it is also common practice in SEM to cross validate the model with a different and independent sub sample. This approach applies in both SEM type, partial least squares and covariance based SEM. In this regard, Chin and Todd (1995) assert:

"Cross validation addresses the question of how well a solution obtained by fitting a model to a given sample will fit an independent sample from the same population. It typically begins by randomly splitting a sample into two subsamples. This provides two independent subsamples sharing similar statistical properties. One subsample then is used as a calibration set for model parameter estimation" (p. 238).

In approaching PLS, it is often necessary to split the data set that will be used in model assessment, i.e. initial model and revised model (Ghiselli, Campbell & Zedeck, 1981; Fornell, 1982). The commonly used method is to divide samples with odd and even case numbers (Igbaria, 1993; Igbaria, Guimaraes & Davis, 1995). In this study data was divided into two subgroups – sample 1 (S1) and sample 2 (S2) as conducted in prior studies, for instance Amoroso and Cheney (1991), Igbaria (1993), and Igbaria et al. (1995). No a-priori reason suggests the presence of systematic differences between both data sets (Igbaria, 1993; Igbaria, Guimaraes & Davis, 1995). Sample 1 represents all cases with odd identification numbers, while sample 2 consists of all cases with even identification numbers. As seen in Figure 3, sample 1 was used twice. Firstly, it was used to test item

⁵ Further discussion on this particular issue can be seen in Chin (1998a, 1998b).

reliability of the initial model. Secondly, it was used again to assess the initial model in terms of both measurement properties and structural path. The important statistics of the measurement model are item reliability, internal consistency, Average Variance Extracted (AVE), square-root of AVE and cross loadings (Barclay, Higgins & Thompson, 1995). The first three tests are known as convergent validity (Fornell & Larcker, 1981) and the last two tests are known as discriminant validity (Barclay, Higgins & Thompson, 1995).

Following Igbaria (1993) and Igbaria et al. (1995), the procedure followed in this paper will ensure that only reliable and valid mea-

asures of construct being used to obtain conclusions regarding the nature of relationships among constructs (Barclay, Higgins & Thompson, 1995; Hulland, 1999). Data analysis procedure as shown in Figure 3 suggests that research model assessment is started with an item reliability assessment of the initial model using sample 1. In particular, the first step aims to examine the simple correlation (also known as item loading or λ) between items and their respective constructs. Based on the results of item reliability assessment, the first revision of the initial model is made. In doing so, items with low loading may be dropped from the model. The model is then evaluated in the subsequent stage.

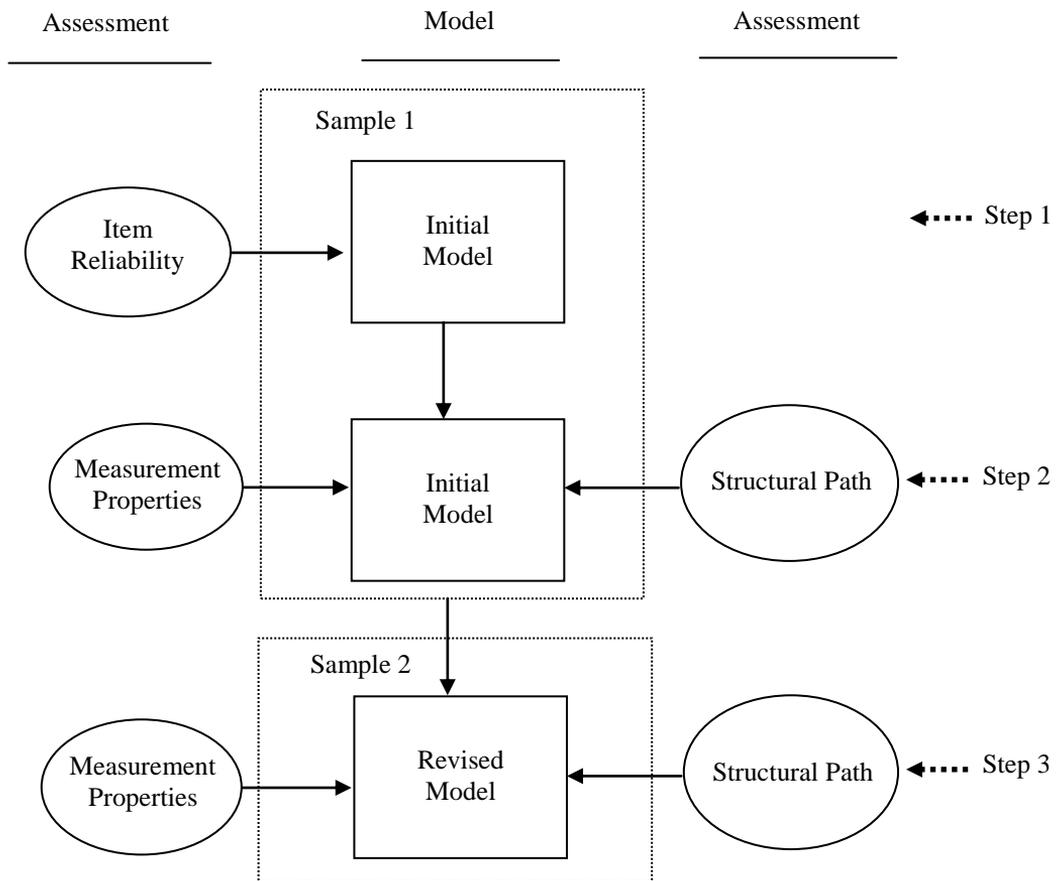


Figure 3 Data Analysis Procedure

In step 2 (Figure 3), sample 1 is used once again to test the measurement properties and structural path of the initial model. The assessment of measurement properties involves the convergent validity tests (item reliability, internal consistency and average variance extracted) and discriminant validity (square-root of AVE and cross loadings). Structural path assessment, which involves resampling procedures using the bootstrapping method, includes examination of path coefficient (γ) and R-square. The difference between step 1 and step 2 in the Figure 3 is that step 1 only assesses the reliability of all items. As a consequence, only reliable items are used in step 2. On the other hand, step 2 encompasses measurement properties and structural path assessments. It is noted that item reliability is part of the measurement properties. After step 2, unreliable items, non-significant paths as well as the corresponding construct may be dropped from the model. As a result, this stage comes up with the revised model that will be evaluated in step 3.

Finally, the second data set (sample 2) is used to evaluate the revised model in step 3. The tests of measurement and structural path are performed again at this stage. As in the initial model, the structural path and overall model are evaluated in terms of the significance of path coefficients and explanatory power. Resampling procedures such as bootstrapping, which produces t -statistics, is used to assess the significance of structural paths (Chin & Newsted, 1999). In addition, the model's explanatory power is assessed by the R^2 values for the endogenous variables (Fornell & Larcker, 1981). The interpretation of R^2 is the same as R^2 in regression analysis.

MODEL EVALUATION

The model evaluation in PLS is different from the traditional parametric-based techniques. In this regard, Chin (1998b) states:

“Because PLS makes no distributional assumption, other than predictor specification, in its procedure for estimating parameters, traditional parametric-based techniques for significance testing/evaluation would not be appropriate. Instead, Wold (1980; 1982) argued for tests consistent with the distribution-free/predictive approach in PLS. In other words, rather than based on covariance fit, evaluation of PLS models should apply prediction-oriented measures that are also nonparametric” (p. 316).

Therefore, model evaluations that are commonly used in PLS are R -square, bootstrapping/jackknifing, composite reliability, Average Variance Extracted, and cross loadings. These will be discussed further in the following sections.

1. Validity

Two types of validity assessment commonly applied in PLS-based data analysis are convergent validity and discriminant validity.

1.1. Convergent Validity

Convergent validity is defined as “... to whether the items, comprising a scale behave as if they are measuring a common underlying construct” (Davis, 1989, p.327). In the PLS model, convergent validity consists of three tests: item reliability, composite reliability and average variance extracted (hereafter AVE) (Fornell & Larcker, 1981). The first two measures have been explained in the previous section. Another measure is AVE, which is regarded as one of discriminant validity indicators. AVE will be explained further in the following section.

1.1.1 Item Reliability

There are two reliability indicators in PLS, item reliability and composite reliability. The latter is also known as internal consistency.

Both indicators are part of the convergent validity assessment. Item reliability is evaluated by assessing the simple correlation (loadings) of the items with their respective construct (Barclay, Higgins & Thompson, 1995). Although the conservative acceptable reliability is 0.707 (Fornell & Larcker, 1981; Barclay, Higgins & Thompson, 1995), some argue that a value of 0.5 might be regarded as acceptable factor loading as long as there are some other factors in the same construct load highly (Chin, 1998b; Keil et al., 2000). Another guideline by Hair et al. (1998), which use sample size as the basis can also be followed. Further, Hulland (1999) contends that items with loadings of less than 0.4 - 0.5 should be excluded. Further, according to Hulland (1999), a low loading could be caused by (1) wording problems in the questionnaire, (2) improper items, and (3) problems in transferring the research instrument/questions from one context to another context. The latter is concerned with international research methods, which is elaborated in the back-translation process section later in this chapter.

1.1.2 Composite Reliability

The use of multiple observed variables in a latent variable leads to concerns regarding not only item reliability, but also to the extent to which the underlying construct is free from random errors. Composite reliability, which is also known as internal consistency (Fornell & Larcker, 1981), is commonly reported in structural equation modeling as the measure of reliability of particular construct. According to Chin (Fornell & Larcker, 1981; Chin, 1998b; Barclay, Higgins & Thompson, 1995), the value of composite reliability can be determined using the following formula:

$$\rho_c = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum_i \text{Var}(\varepsilon_i)}$$

The notation of ρ_c in the formula means composite reliability ("c" stands for composite), where λ_i is the simple correlation/loading

between items and their construct, and $\text{Var}(\varepsilon_i) = 1 - \lambda_i^2$. The interpretation of composite reliability value is similar to Cronbach's alpha in which 0.7 is also used as the benchmark (Barclay, Higgins & Thompson, 1995). The difference between Cronbach's alpha and composite reliability is that the latter does not assume Tau equivalency (Chin, 1998b; Barclay, Higgins & Thompson, 1995). In other words, composite reliability does not presume that each item/observed variable contributes equally to the construct as in Cronbach's alpha. In addition, low composite reliability value could reflect the presence of poor construct definition and/or construct multidimensionality (Hulland, 1999).

1.1.3 Average Variance Extracted (AVE)

Average Variance Extracted, which is a convergent validity measure aims to assess the variance explained by the items compared to the variance due to measurement error (Chin, 1998b). Chin (Fornell & Larcker, 1981; Chin, 1998b; Barclay, Higgins & Thompson, 1995) suggest that the value of AVE can be obtained using the following formula:

$$\text{AVE} = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum_i \text{Var}(\varepsilon_i)}$$

where λ_i is the item loading and $\text{Var}(\varepsilon_i) = 1 - \lambda_i^2$. AVE can be interpreted as a more conservative reliability assessment. For adequate reliability, a given construct should attain at least a value of 0.5 (Fornell & Larcker, 1981). Otherwise, its reliability will be problematic and the construct is questionable (Fornell & Larcker, 1981).

1.2. Discriminant Validity

Discriminant validity refers to the extent particular constructs in the same model differ from each other (Barclay, Higgins & Thompson, 1995). Therefore, a construct should share more variance with its measures than with other constructs, and variance due to

measurement error should be lower than the variance explained by the construct (Fornell & Larcker, 1981). A PLS model is usually evaluated in terms of discriminant validity using square roots of AVE and/or cross loadings tests.

1.2.1. Square Root of AVE

Square root of AVE is one of the discriminant validity assessments in partial least squares analysis. According to Gefen, Straub & Boudreau (Gefen, Straub & Boudreau, 2000), square-root of AVE is amongst the most reported PLS statistics in the respected MIS journals. To show the discriminant validity, PLS-based papers often report the correlation matrix that encompasses the correlation amongst constructs and the square roots of AVE of each construct (Hulland, 1999). The requirement of discriminant validity is that the square roots of AVE should be larger than correlation of the related constructs (Barclay, Higgins & Thompson, 1995; Fornell & Larcker, 1981). In other words, the diagonal values that indicate square-root of AVE should be larger than the off-diagonal values in the corresponding columns and rows (Hulland, 1999). At the moment, the PLS software available, PLSGraph 3.0, does not produce this statistic. Therefore, it should be measured separately, using other tools such as a spreadsheet.

1.2.2 Cross Loadings

Cross loading measures the correlation of the particular items with all constructs within the model including the construct they are required to reflect (Chin, 1998b). It is another discriminant validity assessment. The criterion is that an item should load more highly to the construct it is required to reflect than to the other construct(s) (Fornell & Larcker, 1981; Chin, 1998b). An item that loads more highly to other construct(s) can be considered to be excluded from the PLS model.

2. R-Square

As in multiple regression analysis, PLS procedures also produce *R*-square to determine the variance in the construct that is explained by the model (Barclay, Higgins & Thompson, 1995). Therefore, *R*-square values will determine the explanatory power of the model. The interpretation of the value of R^2 in PLS is the same as the R^2 produced by regression analysis.

3. Bootstrapping

To assess the statistical significance of the loadings and structural path coefficients, bootstrapping or the alternative, jackknifing procedure, are commonly used in PLS. The use of those non-parametric approaches is due to the data that are not assumed to be multivariate normal in PLS (Barclay, Higgins & Thompson, 1995). Both methods, which are provided in the PLSGraph beta version 3.0, should produce the converged standard errors (Chin, 1998b). The choice between bootstrapping or jackknifing is based on the trade-off between computational time and efficiency (Chin, 1998b). Further, Chin (1998b, p.320) states:

“Jackknife estimation tends to take less time for standard error estimation under the join assumption that the bootstrap procedure utilizes a confidence estimation procedure than those of the jackknife. Conversely, the jackknife is viewed as less efficient than the bootstrap because it can be considered as an approximation to the bootstrap (Efron & Tibshirani, 1993)”.

THE LIMITATIONS OF PLSGRAPH SOFTWARE

As explained before, the availability of software to perform partial least squares technique is limited. PLSGraph, which is still in beta version, is easier to use and no programming is needed. Despite its advantages, there are some limitations

encountered by author during the interactions with the beta version of PLSGraph:

- ❑ It may need an extensive hard disk memory. The unsuccessful Jackknifing procedure may take about 1-2 Gigabyte of hard disk memory depending of the nature of the data. Further, it might not be able to clean the memory (hard disk) unless to reinstall the operating system i.e. Windows. This problem will be more severe when bootstrapping is undertaken using 500 sub-samples. The hard disk may be full within a few iterations. The unsuccessful Jackknifing procedure mostly due to the lack of RAM, hard disk memory and slow computer processor.
- ❑ It needs faster computer processor. Based on the author's experience, the faster outcome can be obtained using computer processor that is equivalent to Pentium III or above. The use of Celeron processor is not recommended, because it may be slow and often fail to provide Jackknifing output.
- ❑ Raw data has to be in the form of raw (txt) file. The file can be created by either manually enter the data (this option takes time and the risk of mistyping is high) or to entry the data into the SPSS first, then convert into txt file by saving as fixed ASCII (dat file). After that, the file is opened and edited using MS Word (using "find and replace" automatic function to clean space and tab characters). Finally, the data is copied and pasted into blank raw data file (or txt file) and then saved as raw file. Actually researcher can use any software and technique as long as the output is txt file or raw file.
- ❑ PLSGraph does not provide composite reliability and AVE results. Researcher, therefore, has to compute these validity indicators using other tools such as spreadsheet.
- ❑ Another problem is related to cross loadings procedure. At the moment

PLSGraph (beta version 3.0) does not provide cross loadings results. This is the most complicated procedure in PLSGraph, because to some extent researcher has to compute cross loadings manually. To do so, researcher can follow the instructions provided by Wynne Chin in <http://disc-nt.cba.uh.edu/chin/#q3>. Based on the Chin's explanation, the author suggests that there are three software involve in the computation. Firstly, PLSGraph is needed to provide data matrix (in PLSGraph, click 'options' – 'output' – 'final results:' – choose 'data matrix'). Secondly, MS Word is used to edit the data matrix and produce the txt file. Finally, the txt file is converted into SPSS (sav file). The cross tab technique is performed to produce the final results (in SPSS, click 'analyze' – 'descriptive' – 'cross tab').

Concluding Remarks

Partial least squares as an alternative to covariance-based SEM may be considered by researchers. The use of PLS is expected to overcome some limitations inherent in covariance-based SEM, such as large sample requirement, data normality and reflective indicators. PLS also has less extensive set of statistics than covariance-based SEM. Although PLS promises some benefits, it also has weaknesses. The availability of PLS tool is among the important one.

To conclude, this paper discusses some issues concerning PLS. It provides initial understanding regarding partial least squares and its relationship with SEM. Another contribution of this paper is that it will enable researchers to apply appropriate SEM method that relevant with the nature of data and research model. As highlighted by Cohen et al. (1990), inappropriate use of SEM may lead to serious questions regarding results and interpretation of study. Finally, this paper is not without weaknesses. There are many issues that are debatable and issues that have not been

covered in this paper. Further study and discussion may be useful to provide a more comprehensive understanding of PLS as well as SEM. For those who are interested to know more about SEM or want to share ideas about SEM can join with the Structural Equation Modeling Discussion Network (SEMNET), which can be found in the following website: <http://www.gsu.edu/~mkteer/semnet.html>.

REFERENCE

- Amoroso, D. L. & Cheney, P. H. (1991), 'Testing a Causal Model of End-User Application Effectiveness', *Journal of Management Information Systems*, vol. 81, no. 1, pp. 63-89.
- Barclay, D., Higgins, C. & Thompson, R. (1995), 'The Partial Least Squares (PLS) Approach to Causal Modeling: Personal Computer Adoption and Use as an Illustration', *Technology Studies*, vol. 2, no. 2, pp. 285-309.
- Chin, W. W. (1998a), 'Issues and Opinion on Structural Equation Modeling', *MIS Quarterly*, vol. 22, no. 1, pp. vii-xvi.
- Chin, W. W. (1998b), 'The Partial Least Squares Approach to Structural Equation Modeling', in *Modern Methods for Business Research*, ed. Marcoulides, G. A., Lawrence Erlbaum Associates, Inc., Mahwah - NJ, pp. 295-336.
- Chin, W. W. & Newsted, P. R. (1999), 'Structural Equation Modeling Analysis with Small Sample Using Partial Least Squares', in *Statistical Strategies for Small Sample Research*, ed. Hoyle, R. H., Sage Publication, Inc., Thousand Oaks - California, pp. 307-341.
- Chin, W. W. & Todd, P. A. (1995), 'On the Use, Usefulness, and Ease of Use of Structural Equation Modeling in MIS Research: A Note of Caution', *MIS Quarterly*, vol. 19, no. 2, pp. 237-246.
- Cohen, P., Cohen, J., Teresi, J., Marchi, M. & Velez, C. N. (1990), 'Problems in the Measurement of Latent Variables in Structural Equations Causal Models', *Applied Psychological Measurement*, vol. 14, no. 2, pp. 183-196.
- Davis, F. D. (1989), 'Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology', *MIS Quarterly*, vol. 13, no. 3, pp. 319-340.
- Efron, B. & Tibshirani, R. J. (1993), *An Introduction to the Bootstrap (Monograph on Statistics and Applied Probability, #57)*, Chapman & Hill, New York.
- Fornell, C. (1982), *Second Generation of Multivariate Analysis*, Praeger, New York.
- Fornell, C. & Bookstein, F. L. (1982), 'Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory', *Journal of Marketing Research*, vol. XIX, no. November, pp. 440-452.
- Fornell, C. & Larcker, D. F. (1981), 'Evaluating Structural Equation Models with Unobservable Variables and Measurement Error', *Journal of Marketing Research*, vol. XVIII, no. February, pp. 39-50.
- Gefen, D., Straub, D. W. & Boudreau, M.-C. (2000), 'Structural Equation Modeling and Regression: Guidelines for Research Practice', *Communications of the Association for Information Systems*, vol. 4, no. 7, pp. 1-77.
- Ghiselli, E., Campbell, J. & Zedeck, S. (1981), *Measurement Theory for the Behavioral Sciences*, W.H. Freeman, San Francisco.
- Hair, J. F., Anderson, R. E., Tatham, R. L. & Black, W. C. (1998), *Multivariate Data Analysis*, 5th edn, Prentice-Hall Inc., Upper Sadle River, New Jersey.
- Hulland, J. (1999), 'Use of Partial Least Square (PLS) in Strategic Management Research: A Review of Four Recent Studies', *Strategic Management Journal*, vol. 20, no. 2, pp. 195-204.

- Igbaria, M. (1993), 'User Acceptance of Microcomputer Technology: An Empirical Test', *Omega*, vol. 21, no. 1, pp. 73-90.
- Igbaria, M., Guimaraes, T. & Davis, G. B. (1995), 'Testing the Determinants of Microcomputer Usage via a Structural Equation Model', *Journal of Management Information Systems*, vol. 11, no. 4, pp. 87-114.
- Igbaria, M., Zinatelli, N., Cragg, P. & Cavaye, A. L. M. (1997), 'Personal Computing Acceptance Factors in Small Firms: A Structural Equation Model', *MIS Quarterly*, vol. September, pp. 279-302.
- Keil, M., Tan, B. C. Y., Wei, K.-K., Saarinen, T., Tuunainen, V. & Wassenaar, A. (2000), 'A Cross-Cultural Study on Escalation of Commitment Behavior in Software Projects', *MIS Quarterly*, vol. 24, no. 2, pp. 299-325.
- Khalifa, M., Limayem, M. & Liu, V. (2002), 'Online Consumer Stickiness: A Longitudinal Study', *Journal of Global Information Management*, vol. 10, no. 3, pp. 1-14.
- Lohmoller, J.-B. (1988), 'The PLS Program System: Latent Variables Path Analysis with Partial Least Squares Estimation', *Multivariate Behavioral Research*, vol. 23, pp. 125-127.
- Wold, H. (1980), 'Model Construction and Evaluation when Theoretical Knowledge is Scarce: Theory and Application of Partial Least Squares', in *Evaluation of Econometric Models*, eds. Kmenta, J. & Ramsey, J. B., Academic Press, New York, pp. 47-74.
- Wold, H. (1982), 'Soft Modeling: The Basic Design and Some Extensions', in *Systems under Indirect Observation: Causality, Structure, Prediction*, vol. 2, eds. Joreskog, K. G. & Wold, H., North Holland, Amsterdam, pp. 1-54.