Original Research Article

PERMUTATION TEST, NON-PARAMETRIC, AND CONFIDENCE SET APPROACHES TO MULTIGROUP ANALYSIS FOR COMPARING 2 GROUPS USING PARTIAL LEAST SQUARE STRUCTURAL EQUATION MODELING (PLS-SEM)

ABSTRACT

Partial Least Square Structural Equation Modeling (PLS-SEM) is become prominent as alternative of Covariance Based Structural Equation Modeling (CB-SEM) due to the technique employ is much comfortable. Thereby, this research paper intend to present guide to carry on the Partial Least Square to Multi-Group Analysis (PLS-MGA) using categorical variable. In particular, the discussion of PLS-MGA is comprised of three approaches namely permutation test, non-parametric test, and non-parametric confidence set interval. All of these test are established as non-parametric test in which do not relies of statistical assumption. Thus, this paper work is aimed to determine which approach is much comfort to apply so as to present the guide for readers. Moreover, the practice of Square Multiple Correlation (R^2) also has been promoted to identify the importance and performance of each exogenous constructs applied. Once executed three approaches on the same data, two approaches namely permutation test and non-parametric test suggest all of these exogenous constructs applied cannot be moderates via gender group between exogenous and endogenous constructs. In addition, the capability of R^2 is proved can be extended to determine the importance and performance of independent variables. Ultimately, this paper work is success to achieve all the issues addressed.

Keywords: Partial Least Square Structural Equation Modeling (PLS-SEM), Covariance Based Structural Equation Modeling (CB-SEM), Partial Least Square to Multi-Group Analysis (PLS-MGA), permutation test, non-parametric test, non-parametric confidence set interval test, Square Multiple Correlation, Categorical variable, importance and performance.

Introduction to CB-SEM

Recently, most of the researchers and scholars interest to implement their research using Variance Based Structural Equation Modeling (VB-SEM). Variance based structural equation modeling is perceived to overcome the limitation of Covariance Based Structural Equation Modeling (CB-SEM) in many aspect and perspective. Thus, the prevalence of this particular method has become a preferences for many areas especially for social science discipline.

In particular, the strength of this method can ascertain the scholar to execute their analysis with less complicated and cumbersome. Henseleret. al (2012) established SmartPls 2.0 to carry on the VB-SEM approach and several articles has been published by many prominent researchers such asSarstedt, Ringle, Hair, Chin and Dibbern. According to Afthanorhan (2014), VB-SEM is can be known as Partial Least Square Structural Equation Modeling (PLS-SEM) that has been introduced by Wold (1982) and been modified to improve the capability of PLS-SEM by Lohmoller (1989). However, PLS-SEM is less popularity compare to CB-SEM in that time since there still a lot or argument to defend PLS-SEM especially for the assessment of fitness.

Thereby, most of the researchers modified this method to become more meaningful to overcome the limitation of CB-SEM. Previously, CB-SEM is perceived to be the best method for the research and quantitative analysis since the method applied provide more assessment and obey the statistical assumption provided. For instances, CB-SEM does not assume of all the items included in a model to be compute of mean but instead to analyze the research more holistic and comprehensive beyond of other methods introduced. In some other researcher often compute the mean of items for each variable to help them analyze their research rather than to deal for each items in line the statistical assumption given.

In particular, CB-SEM have two types of model whereby measurement model and structural modelregarding to our objective research. Basically, measurement model is commonly used for Confirmatory Factor Analysis (CFA) to confirm which items in each construct should be retained for the subsequent steps which is structural model (Afthanorhan, 2014). In this case, the scholars were served a vary of assessment of fitness as a gauge for each measurement to justify their fitness. According to Ringleet. al (2012), the fitness of model capable to provide a meaningful finding for the structural model.

Moreover, CB-SEM is generally been used to minimize the correlation matrix and at the same time to stress on the covariance in a model (Hair, 2012). The procedure for this method is quite manly for evaluation process rather than the prediction process. In fact, the scholars more interested to carry on their research based on the prediction obtained. Besides, this particular method is useful the parametric distribution. The parametric is considered for normal data solely withoutemphasized on non-normal data. In generals, CB-SEM needs at least 100 sample size to attain a meaningful findings. Otherwise, the result suggested would become ambiguities and of course affect the prediction process (Afthanorhan, 2014). All of these issues become wider and restricted for scholar to investigate their analysis more profound.

Introduction to PLS-SEM

Once the scholar pledges the limitation of CB-SEM in some circumstances, PLS-SEM began capture an attention among scholar to settle their problem faced. PLS-SEM is used to focus on variance that has been capture in a model and overestimate the indicator loadings (Sarstedt, 2014). In other words, if the scholar had insufficient to provide a better assessment for measurement model, PLS-SEM will be the one to solve that kind of problems. Indeed, PLS-SEM has still lack of fitness that will be suggested for Confirmatory Factor Analysis (CFA) due to restricted for incremental of fitness.

Thus, some of the researchers suggested that the CB-SEM and PLS-SEM were plays an important role to provide a better findings. In some research papers, the CB-SEM was always preferred to evaluate the measurement model (CFA method) to evaluate the fitness of model. In other words, CFA fitness model is the first stage that should be proceeding earlier to enter the next level. Afterwards, PLS-SEM can be used in this level to achieve the objective research based on inquires of scholars. According to Hair (2012), PLS-SEM and CB-SEM were supposed to be complementing each other rather than to discriminate each approach.

Moreover, PLS-SEM is more comprehensive to be used once the scholars and practitioners failed to satisfy the statistical assumption stipulated. For instances, if the scholars deal with the serious case to attain the large sample size in order to implement the path analysis using structural equation modeling for their research, PLS-SEM will be a great help to solve that problems.

Usually, the large sample size would be considered for parametric distribution (Afthanorhan, 2014) but small sample size can be handled using PLS-SEM (Ringle et.al, 2014). In this instance, PLS-SEM used the bootstrapping technique based on the Monte Carlo simulation to resampling the calculation of parameter for each dataset. According to Ringleet. al (2014), 5,000 samples are needed to obtain the best finding. In other words, PLS-SEM is not the kind of method to assume for each model is normally distributed but supposes to execute the bootstrapping technique to normalize the dataset. According to Byrne (2010), bootstrapping techniques is an aid to transform the non-normal data set to be normal distribution. Thus, this statement is adequate to strengthen the capability of bootstrapping employ in PLS-SEM.

Hence, t-test is prevailed for testing the significant level of causal effect between explanatory and dependent variables conformity of terms sample size suggested. Previously, t-test is proved to be a best way to determine the significant level for small sample size (Arshad et.al, 2010). Indeed, t-test can harm the findings if the particular method isimplementing for the large sample size but since the present of bootstrapping technique in PLS-SEM is quite significant to convince the efficiency of t-test for testing significant level. Thus, the scholars whom implement PLS-SEM rely on t-test to capture the significant level for each model designed.

In seek of enjoyment to PLS-SEM, a vary method have been proposed based on their research work. This habit is not inevitably in social science, management and marketing disciplines especially for the academicians.The path analysis of PLS-SEM could be extending to be more importance once this package offers the Importance-Performance Matrix Analysis (IPMA) to identify the importance and performance for each factor. Consequently, the research more meaningful and better understanding to ascertain the managerial make a decision in terms of values of their research.

PLS-SEM has become increasingly preferred especially when comes for the analysis that involve a higher constructs. In particular, PLS-SEM also offers a user-friendly to develop a structural model that has potential to become as reflective or formative constructs. In fact, CB-SEM also managed too but the mechanism to be used is quite cumbersome and takes time to do so. Thus, most of the researchers intend to apply PLS-SEM for distinguish the role of reflective and formative constructs (Afthanorhan, 2014).

Besides, PLS-SEM also introducing to segmentation approach that basically been used among the marketing and management sector to identify a number of segment and type of existence for each segment. In PLS-SEM, Finite Mixture Partial Least Square Structural Equation Modeling (FIMIX-PLS) is the only one segmentation method constituted (Ringle, 2012). This aforementioned method is perceived more relevant rather than Response Based Segmentation (REBUS-PLS). For the common knowledge, CB-SEM do not provide the segmentation classes instead targeted on path analysis solely.

In statistical research, most of the researchers interest to advance their research pertaining to distinguish of the categorical variable (e.g.: gender, race, education, salary and status) on their model. This model recognized as modeling moderation but the method used been classify as multi-group analysis (Afthanorhan, 2014). Multi-group analysis encouraged the scholar to probe their research more profound and extensive so as to capable expands their research in a higher level. In addition, the findings would become more interesting and inclusiveness to determine whether of categorical variable (moderator variable) has a potential to influence the causal effect. In this case, the authors employ the gender (male and female) to moderate the causal effect.

Truly, there are five approaches established to decide the probability level to Partial Least Square Structural Equation Modeling Multi-Group Analysis (PLS-MGA) such as permutation test (Chin, 2003), non-parametric test (Ringle, 2014), parametric test for equal variances (Ringle, 2012; Afthanorhan, 2014, N.Kock, 2014), parametric test for unequal variances (N.Kock, 2014; Afthanorhan, 2014), and Henseler test (Henseler, 2010). However, the aim of this research paper to guide the readers to generate the permutation and non-parametric approaches to PLS-MGA.

THEORETICAL FRAMEWORK

Theoretical framework is the most important thing that should be focused once we want to determine the objective research. As aforementioned, the four exogenous construct are pointing outwards to one endogenous construct. Repeatedly, all of these construct should be established by literature review, in particular, the study is prevailed to determine the youth perception towards volunteerism program. The failed supporting of our research might produce inaccurate. The Figure 1 shows the theoretical framework as follows:

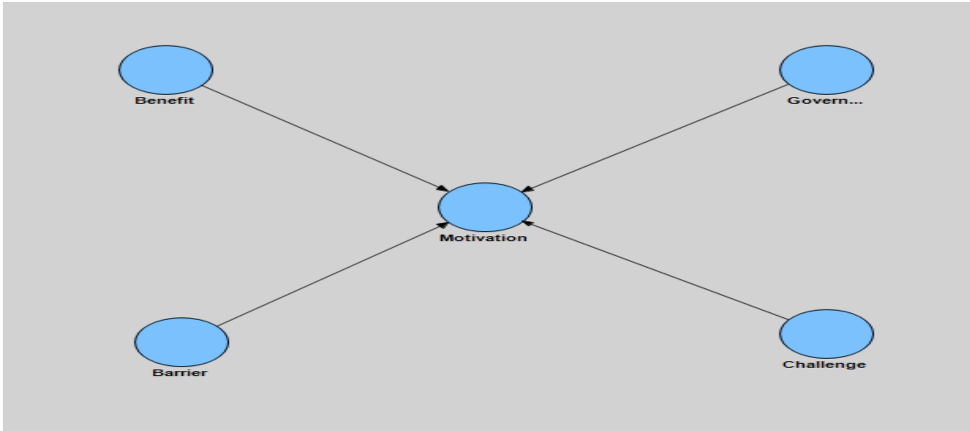


Figure 1: Theoretical Framework

Parametric Test for Equal and Unequal Variances

Parametric test is basically for the normal data and the findings will become imprecise if the scholar apply the contradict assumption (Afthanorhan, 2014). This aforementioned approach was initially by Keil (2000) and then has been extended by Chin (2003) to ensure the accurate analysis for probability level. In PLS-SEM, the normality test is not provided since the applied method is useful for various data. In other words, the parametric and non-parametric test is allowed to be conducted in order to achieve the required objective research (Afthanorhan, 2014). However, the implementation of PLS-SEM does not assume all the data constituted are normal.

Thus, the bootstrapping technique is assists researchers gain the normal data. In previous research, the authors had published the guide for parametric test that comprised of equal and unequal variances. The equal variance assumption is important in determining which appropriate statistical test to be use. Thus, the box-plot test had provided in some packages such as SPSS, MINITAB, and Eviews to help the researchers to identify the types of variances. According to NCSS statistical software chapter 206, if the data are non-normal, the modified Levene test can be a great helpful for many non-normal situations. Some researchers recommend against using a preliminary test on variance in which do not have a strongly supported to stand the findings. Thus, if the scholars decide to against these preliminary test, the ratio of the sample sizes (larger sample size over the smaller sample size) is equal to or greater than 1.5 is considered as unequal variance t-test (Ott, pg.144, 1984).

Afthanorhan (2014) stated that several steps to guide the scholars undertake their research. List of steps is stated as below for the equal unequal variances:

1. Build of latent construct according to the theoretical framework.
2. Assign the data according to gender group (Male=1, Female=2)
3. Permute the structural model based on specified groups
4. Execute PLS algorithm for each specified groups.
5. The t-statistics for each groups will be carry on to the next steps
6. Calculate the probability level based on the Keil (2000) and Chin (2003) formulae for equal and unequal variances t-test.
7. P-value less than 0.50 considered significant paths (Reject null hypothesis).
8. The p-level for both tests should be same even carry the different of beta coefficient.

The main of this research paper to address on the permutation and non-parametric test. Thus, the guide of this test will be illuminate with the illustration of formula and figures.

Permutation Approach

In this case, the paper address on the permutation approach. Permutation test can be known as randomization test that does not rely on statistical assumption to attain the normal data. A randomization test is conducted by enumerating all possible permutations of the groups while leaving the data values in the original order. In this case, the groups will be test is gender groups (male and female). The difference is calculated for each permutation that provided in each specified groups and the number of permutation that result in a different with a magnitude greater than or equal to the actual difference is counted. This test is freely distribution since the test is stipulated by self-researchers. The proportion should be counted based the number of permutations tried gives the significant level of the test.

According to Edgington (1987), at least 1,000 permutation by selected should be counted. Besides, Ringleet. al (2014) suggest to permute by 5,000 permutation since the bootstrapping technique will be calculate in the slower rate. In this case, the author also uses the same scale of Ringle to provide all the possible permutation. The steps in permutation are almost the same as previous approach since only has different in obtaining of probability level. List of steps are stated as below:

1. Build of latent construct according to the theoretical framework.
2. Assign the data according to gender group (Male=1, Female=2)
3. Permute the structural model based on specified groups
4. Execute PLS algorithm for each specified groups.
5. The output of path coefficient for each specified groups will be appear in default report.
6. Extract the value of path coefficient (Original Mean) for each path in structural model of specified groups (Male and Female).
7. Calculate the difference of each specified groups (e.g: $|\pi_{male}-\pi_{female}|$)
8. Calculate the probability value (p-level) based on this formula below:

$$\text{P-level} = \frac{(\text{No.ofT}-\text{test of specified groups} > T-test\ of\ model)+1}{(\text{Total of T}-\text{test of specified groups}+1)}$$

Non-Parametric Approach

Previously, the authors had published one article regarding on the parametric approach to multi-group analysis using PLS-SEM. However, the methodology used is inappropriate since the applied method (PLS-SEM) is a non-parametric approach. Thus, the practice of parametric approach to multi-group analysis is quite unfair to determine the significant of causal effect when comparing two groups in structural model. Consequently, the authors provide non-parametric approach based on Ringleet. al (2012) proposed.

There are several steps provided to guide the scholars attain their analysis regarding on the non-parametric approach to multi-group analysis:

1. The database is split in two according to the moderating variable. In this case, the authors choose gender variable to assign for each database (e.g: Male and Female)
2. Run the PLS path modeling algorithm separately for each group (male and female)
3. The two implied parameters B1 and B2 are estimated in those samples. In this case, the authors had 159 cases for male and 293 for female. Once to execute the bootstrapping technique to attain the probability level for each constructs in structural model, 5,000 sampling would be a great used.
4. Using bootstrapping, J estimation of the above mentioned parameters in each sample.
5. Thus, the significance of the test alpha, the probability would be wrong if we reject the null hypothesis that the population parameter B2 in group 2 (Female) is higher to the population parameter B1 in group one (Male) one can be calculated as follows (Joaquin Manzano, 2012):

$$\alpha = \Pr(B1 > B2 \mid b1 < b2) = 1 - \sum \frac{x(B1-B2\ 0B1+B2+B2-B1)}{J^2}$$

Where:

$X = 1 \quad x > 0$

$X = 0 \quad x < 0$

B1 = Parameter of Group 1

B2 = Parameter of Group 2

J = Bootstrapping estimation

Basically, this approach is almost the same as Mann- Whitney test which is known one of the non-parametric tests. In other words, the probability that the estimated parameter in group 2 is higher than the estimation of group 1, is 1- α. Henseler (2009) had provide a spreadsheet of Microsoft excel to make the operational the procedure according to his paper. Thus, this research paper presents a step by step approach to non-parametric using this sheet. The name of sheet is PLS-Hubona that can be attaining in Google.

Non-Parametric Confidence Set Approach

Sarstedtet. all (2011) proposed the confidence set approach in which was initiative by Keil et. al (2000) to prevent the deficiencies of methodology. Afthanorhan (2014) stated that the method develop by Keilet. al (2000) is useful for normality data, thus, the independent t-test was conducted. In accordance with this test, the researchers can compare the group specific bootstrap confidence interval, regardless of whether the data are normally distributed or not (Sarstedt et.al, 2011). The procedure is as follows below:

1. The database is split in two according to the moderating variable. In this case, the authors choose gender variable to assign for each database (e.g: Male and Female)
2. Run the PLS path modeling algorithm separately for each group (male and female)
3. The two implied parameters B1 and B2 are estimated in those samples. In this case, the authors had 159 cases for male and 293 for female. Once to execute the bootstrapping technique to attain the probability level for each constructs in structural model, 5,000 sampling would be a great used.
4. Construct the bias –corrected in which 95% is most preferred.
5. If the parameter estimates for a path relationship between exogenous and endogenous construct of group 1 falls within the corresponding confidence interval of group 2, it can be assumed that there are no significant differences between the group specific path coefficients. In other words, if the parameter estimate falls outside of the confidence interval produced, then, it can be assumed that there are significant differences between the specific groups.

Davison &Hinkley (1997) is one of the researcher use this particular approach to carry on their research. Efron (1981) argue that confidence set approach is misleading once the data applied is small sample size. In order to sustain the capability of PLS-SEM to carry on the large data, the double bootstrap is proposed by Henseleret. al (2009). The double bootstrap means comprised of resampling technique outperforms of 5,000 samples. Hair et.al (2011) suggests to use at least 5,000 bootstrap sample would require drawing more than 25 x 10^6 bootstrap samples.

FINDINGS

In this subtopic, the authors interest to address the total variation of each construct once executed separately. In this case, the author have four type of exogenous construct namely Benefit, Government, Challenge, and Barrier and one endogenous construct namely Motivation. These entire exogenous construct had been tested on Motivation respectively. This approach can helps us to identify which one of the factors would contribute the most variation.

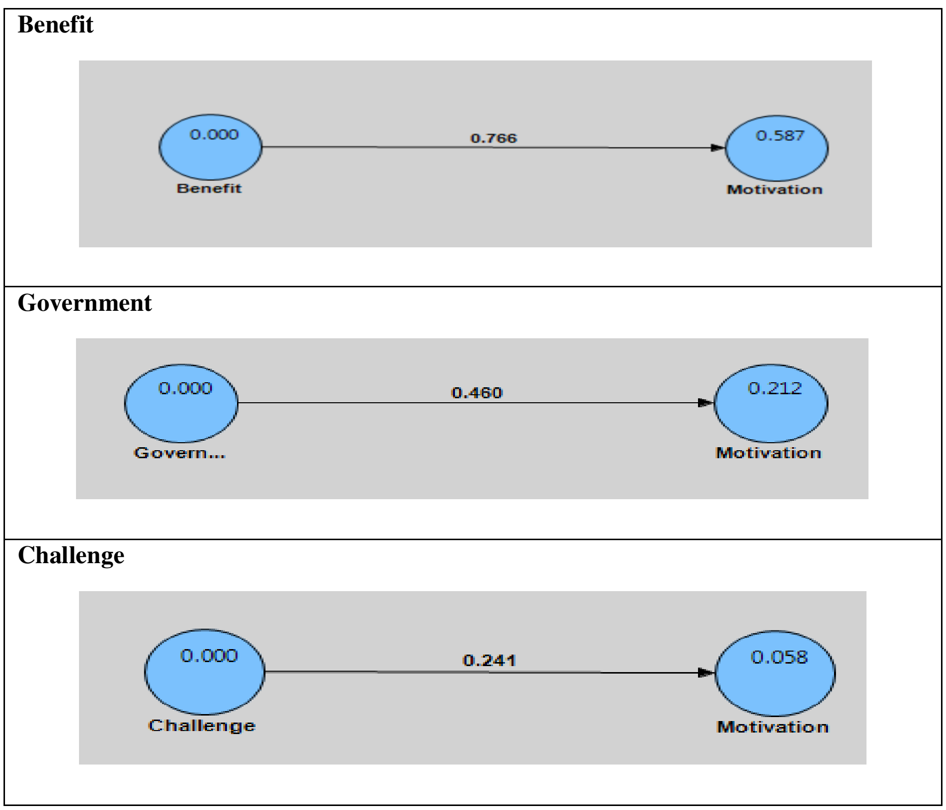
In other words, the higher of the square multiple correlations would be consider high performance. In addition, the importance of each constructs can be indicating based on the causal effect produced between exogenous and endogenous constructs. All of these construct had been executed with the same skills to provide the results. In Table 1 have present four types of figures which represent of each constructs.

Based on the result presented, Benefit construct is identified as the most importance and performance since the causal effect and square multiple correlations are the highest respectively. Of addressing the significance total variation, the interpretation should be stressed on the same thing towards other factors. In this instance, Challenge factor is expected to be the poorest performance and less importance. Thus, this research may be able to be extending to promote the capability of Benefit factor for the future research.

In particular, square multiple correlations is important to help the managerial make the decision to ensure whether each chosen factor is appropriate to further the studies. To date, all of these factors should be retained since this research had a good reason to support all of this research even some construct provide less contribution.

However, the item that should be retained on each construct should be conformachieve of the statistical assumption which is basically higher than 0.60 of outer loadings. Moreover, the reliability and validity for each construct should be performed in order to prevent inaccurate findings. The accurate finding would perform the meaningful research that has potential to contribute in all areas including of social science, marketing, business, management and other disciplines.

Square Multiple Correlation (R^2)



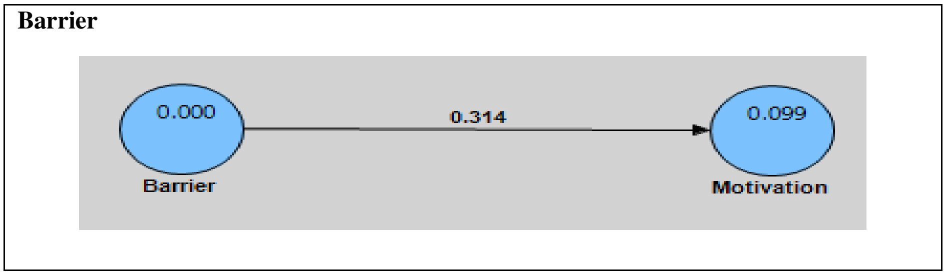


Table 1: Square Multiple Correlation

Then, this research assemble the entire exogenous construct exert on endogenous construct which is namely structural model. In this approach, the authors ensure the assessment of structural model is achieved. For instances, all of the factors achieved the requirement of q predictive relevance (Q) which is higher than 0. Ringle (2005) indicates that the upper 0 means the factors employ in this areas are relevant to researched. Table 2 present the original sample, sample mean, standard error and T-statistics for each path once executed the bootstrapping technique in SmartPls 2.0.

The findings suggest that three out of four construct namely Barrier, Benefit and Government have significant impact on Motivation. Instead, only one path between Challenge factor and Motivation is expected does not has significant impact. In particular, Benefit factor is perceived the most of t-statistics which means that Benefit is the most contributed conformity of square multiple correlation test previously. Afterwards, this research paper will be extending to practice Non-parametric, Non-parametric confidence set interval and Permutation approaches to Multi-group analysis in PLS-SEM.

Full Model	Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	T Statistics (|O/STERR|)
Barrier -> Motivation	0.082066	0.083236	0.031514	2.604121***
Benefit -> Motivation	0.683311	0.681209	0.037681	18.133986***
Challenge -> Motivation	0.017979	0.022381	0.031034	0.579353
Government -> Motivation	0.127794	0.129892	0.035932	3.556564***

Table 2: Full Model

Firstly, the author carries on permutation to multi-group analysis followed by other approaches. All findings related on this approaches are presented in Table 3:

Full Model	Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	P-Value
Barrier -> Motivation	0.082066	0.083236	0.031514	2.604121***
Benefit -> Motivation	0.683311	0.681209	0.037681	18.133986***
Challenge -> Motivation	0.017979	0.022381	0.031034	0.579353
Government -> Motivation	0.127794	0.129892	0.035932	3.556564***
Male	**Original Sample (O)**	**Sample Mean (M)**	**Standard Error (STERR)**	**T Statistics (|O/STERR|)**
Barrier -> Motivation	0.078119	0.0813	0.052801	1.479489
Benefit -> Motivation	0.688298	0.6868	0.064688	10.640206***
Challenge -> Motivation	0.012209	0.0274	0.054873	0.222503
Government -> Motivation	0.124517	0.1250	0.061750	2.016464**
Female	**Original Sample (O)**	**Sample Mean (M)**	**Standard Error (STERR)**	**T Statistics (|O/STERR|)**
Barrier -> Motivation	0.0776	0.0785	0.0398	1.9520**
Benefit -> Motivation	0.6922	0.6890	0.0468	14.7998***
Challenge -> Motivation	0.0134	0.0214	0.0381	0.3518
Government -> Motivation	0.1197	0.1237	0.0447	2.6780***
Permutation Test	**Male**	**Female**	**|Difference|**	**T Statistics (P-value)**
Barrier -> Motivation	0.078119	0.0776	0.000519	0.5556
Benefit -> Motivation	0.688298	0.6922	0.0039	0.3333
Challenge -> Motivation	0.012209	0.0134	0.00119	0.5556
Government -> Motivation	0.124517	0.1197	0.004817	0.5556

A Non Parametric Approach to Multi-group Analysis

Non-Parametric	Male	Female	Error Probability	P-Value
Barrier -> Motivation	0.078119	0.0776	0.518000	0.4820
Benefit -> Motivation	0.688298	0.6922	0.464300	0.5357
Challenge -> Motivation	0.012209	0.0134	0.552800	0.4472
Government ->	0.124517	0.1197	0.127794	0.872206

Motivation				
Non-Parametric Confidence Set Interval	**Male**	**Female**	**Lower and Upper (95% bias corrected)**	**Confidence Interval**
Barrier -> Motivation	0.078119	0.0776	[0.073943,0.083057]	Falls in Range (N.S)
Benefit -> Motivation	0.688298	0.6922	[0.683641,0.694358]	Falls in Range (N.S)
Challenge -> Motivation	0.012209	0.0134	[0.017037,0.025763]	Not in Range (Sig)
Government -> Motivation	0.124517	0.1197	[0.118582,0.128819]	Falls in Range (N.S)

Table 3: Findings of Non-Parametric Test

*: P-level ≤ 0.10; **: P-level ≤ 0.05; ***: P-level ≤ 0.01; N.S: Not Significant; Sig: Significant

Table 3 is not only present the finding of permutation, non-parametric, and non-parametric confidence set interval approaches but the result for each groups including for male and female are laid out. By inspecting through for each approach including the full model, almost approaches suggest the similar findings unless non-parametric confidence set approaches. The first part, the authors separate the full model to be group 1 (Male) and group 2 (Female) and execute using PLS algorithm. PLS algorithm is developed by Lindgren et. al (2005) and the true name is kernel PLS algorithm. But, now this approach has been expand to be known as Wide Kernel PLS algorithm by Meviket. al (2011).

For male group, there are two independent factors namely Benefit and Government have significant impact on Motivation due to the value is absolute greater than 1.96. Previously, the Barrier factor is a significant impact on Motivation before separately. Thus, it can be proved that the significant impact is influenced by characteristics of each group. In other words, Male groups do not have any obstacleto affect the Motivation factor. However, this particular group agrees to indicate that the Benefit and Government can affect their Motivation to prone volunteerism program. In addition, they decide the Challenge factor is do not effect on Motivation. Thus, the related parties should be address that Male group do not have any problem to be active in volunteerism program and they certified this program is good for their country.

For female groups, they have a different view to explain the significant of volunteerism. They agree that Benefit, Barrier and Government can affect their Motivation to participate in volunteerism program. But, they also have a same view with the Male group to suggest that Challenge factor do not affect the Motivation. Thus, the related parties should provide an affirmative action to identify whether this factor may one of the main problems to prevent them active in volunteerism program. Besides, Female groups indicate the Barrier factor is one of the factors hinder them to prone in particular program. This is because some of their parents do not give permission to let their daughter to involve of suggested program.

For permutation test which is one of the free distribution in which do not relies on statistical assumption executed. As aforementioned, permutation test is appropriate to conduct multi-group analysis to identify whether the gender groups is influenced on Motivation. The findings suggest that all of these factors agree the causal effect between exogenous and endogenous constructs do not affect by gender groups. Based on the Table 3, the authors present characteristics of table for permutation test that should be addressed. In this case, original sample (path analysis) for male and female are presented followed by different and probability value. Different values are attained based on the different between mean of male and female respectively. The last column present of probability level that can be calculated based on the previously formula given. This method needsbilateral steps to consider for the whole perspective in order to prevent unfair assumption. The different between male and female can be presented as below:

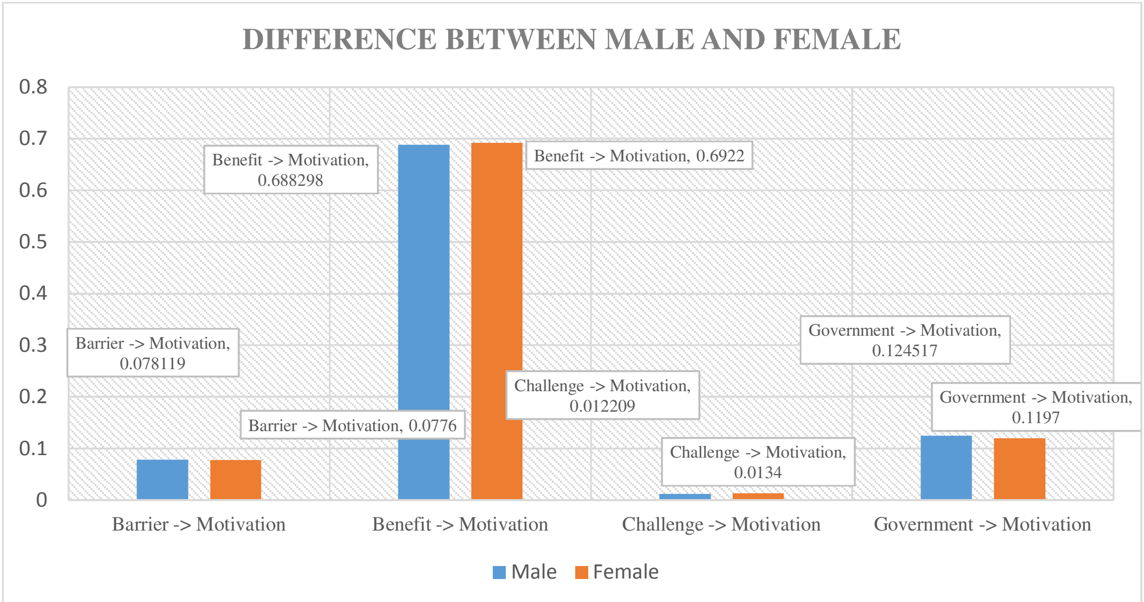
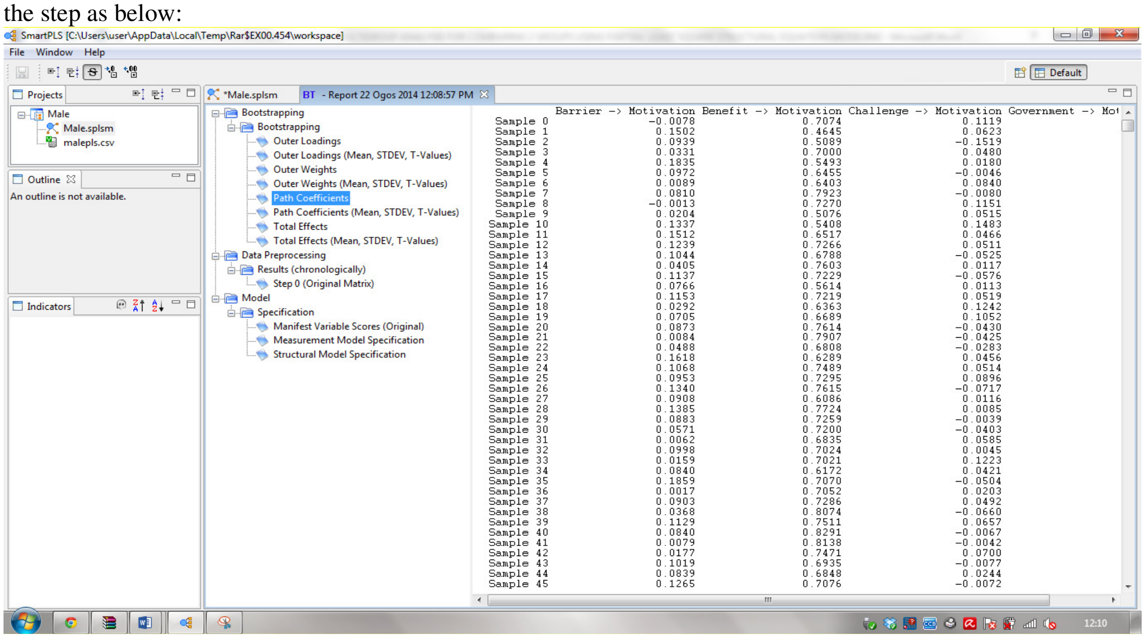


Figure 2: Difference between Male and Female

For non-parametric test to multi-group analysis, the authors also present the original sample mean of male and female same as permutation test. However, the third column is error probability that will be calculated by the PLS-Hubona sheet. The last column is probability level is counted based on the formula: 1-Error Probability. In order to illuminate the step of non-parametric test, the author shows the step as below:



	Barrier -> Motivation	Benefit -> Motivation	Challenge -> Motivation
Sample 0	-0.0078	0.7074	0.1119
Sample 1	0.1502	0.4645	0.0623
Sample 2	0.0939	0.5089	-0.1519
Sample 3	0.0331	0.7000	0.0480
Sample 4	0.1835	0.5493	0.0180
Sample 5	0.0972	0.6455	-0.0046
Sample 6	0.0089	0.6403	0.0840
Sample 7	0.0810	0.7923	-0.0080
Sample 8	-0.0013	0.7270	0.1151
Sample 9	0.0204	0.5076	0.0515
Sample 10	0.1337	0.5408	0.1483
Sample 11	0.1512	0.6517	0.0466
Sample 12	0.1239	0.7266	0.0511
Sample 13	0.1044	0.6788	-0.0525
Sample 14	0.0405	0.7603	0.0117
Sample 15	0.1137	0.7229	-0.0576
Sample 16	0.0766	0.5614	0.0113
Sample 17	0.1153	0.7219	0.0519
Sample 18	0.0292	0.6363	0.1242
Sample 19	0.0705	0.6689	0.1052
Sample 20	0.0873	0.7614	-0.0430
Sample 21	0.0084	0.7907	-0.0425
Sample 22	0.0488	0.6808	-0.0283
Sample 23	0.1618	0.6289	0.0456
Sample 24	0.1068	0.7489	0.0514
Sample 25	0.0953	0.7295	0.0896
Sample 26	0.1340	0.7615	-0.0717
Sample 27	0.0908	0.6086	0.0116
Sample 28	0.1385	0.7724	0.0085
Sample 29	0.0883	0.7259	-0.0039
Sample 30	0.0571	0.7200	-0.0403
Sample 31	0.0062	0.6835	0.0585
Sample 32	0.0998	0.7024	0.0045
Sample 33	0.0159	0.7021	0.1223
Sample 34	0.0840	0.6172	0.0421
Sample 35	0.1859	0.7070	-0.0504
Sample 36	0.0017	0.7052	0.0203
Sample 37	0.0903	0.7286	0.0492
Sample 38	0.0368	0.8074	-0.0660
Sample 39	0.1129	0.7511	0.0657
Sample 40	0.0840	0.8291	-0.0067
Sample 41	0.0079	0.8138	-0.0042
Sample 42	0.0177	0.7471	0.0700
Sample 43	0.1019	0.6935	-0.0077
Sample 44	0.0839	0.6848	0.0244
Sample 45	0.1265	0.7076	-0.0072

Figure 3: Male (Bootstrap)

1. Split data into two groups (Male and Female) and execute respectively. In this case, the authors start on male groups and the result were appeared in default report.
2. Then, execute Bootstrap technique to obtain the standard error and T-statistics for male group.
3. The result was presented for each path and sample. In the first column is present Barrier →Motivation. Thus, the scholars should copy the first column and paste in the column of 100 bootstrap values of group 1.

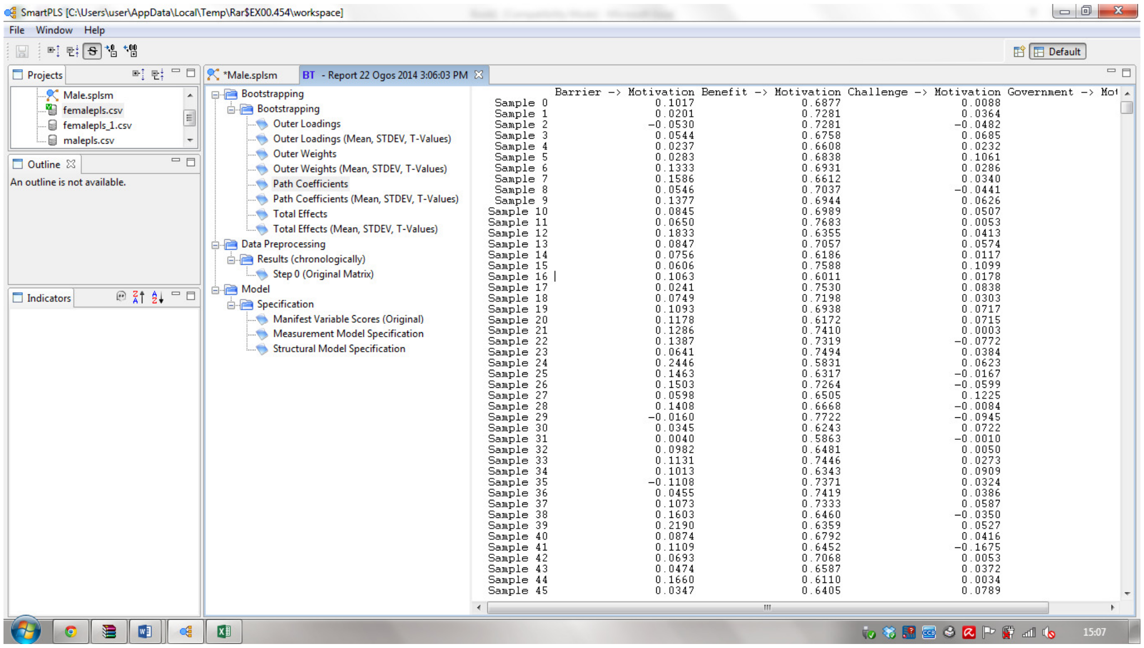


Figure 4: Female (Bootstrap)

1. The process for female group is similar as male group.
2. Since the authors copy Barrier→Motivation from Male data, thus, the same factor should be addressed and paste in 100 bootstrap values of group 2.
3. Parameter of group 1 represent for original mean of Male group as well as for Female group for parameter group 2.
4. Figure 5 present an example of PLS-Hubona to execute the non-parametric multi-group analysis as follows:

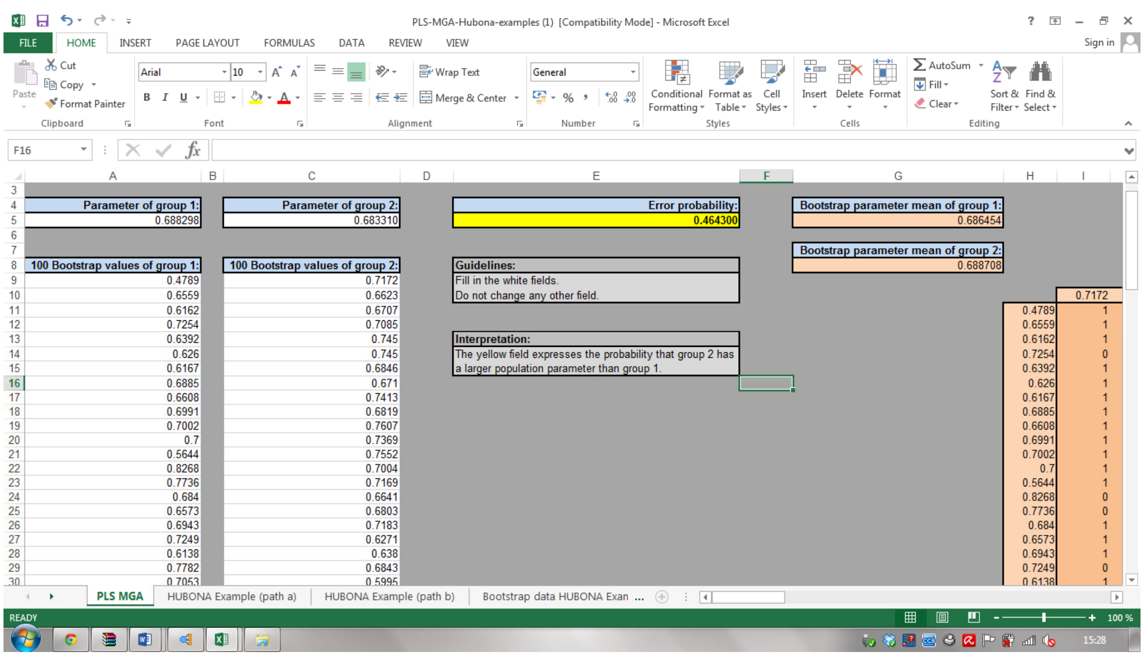


Figure 5: Non-Parametric Test

For Non-parametric confidence set interval test, only one out of four independent factor is indicate has a significant impact on Motivation which is Challenge factor. By inspecting through for each approaches applied, non-parametric confidence set interval test is the only one suggests the difference result. Thus, it can be perceived that the different approaches will effect of our finding to carry on the research more profound. However, this approach is agreed to indicate that the other factor are do not significant impact in line of previous approaches.

Example of Barrier→ Motivation in Group 2 (Female):

Average Mean: 0.0785
Standard Error: 0.0398
Sample Size for female group: 293
95% confidence level = 1.96 (Refer z-test table)
Confidence Interval: $\frac{0.0398}{\sqrt{293}}$ = 0.002325;
= 0.002325 x 1.96 (95% confidence level)
Margin = 0.004547
Upper Interval: 0.0785 + 0.004547 = 0.083057
Lower Interval: 0.0785 – 0.004547 = 0.073943

→ The process of other exogenous constructs is similar as above.

CONCLUSION

This research paper intends to carry on the multi-group analysis using three proposed approaches namely permutation test, non-parametric test, and non-parametric confidence set interval. To date, the authors use the same data by the distinct approaches to determine whether these approaches would provide the same or different findings. All of these approaches are known non-parametric, means that, they do not relies any statistical assumption and freely for researchers to further their studies. Moreover, the authors interest to present the scholar on how to implement these approaches so that the readers know very well which approach is easy to implement based on their knowledge.Based on our experience and observation, non-parametric confidence set approach is the easiest way to provide the probability level rather than the other approaches. However, if the other researcher interest to apply non-parametric test, the scholars are advised to attain the spreadsheet of Henseler (2009) to ascertain them carryon their research. Moreover, the permutation test also can be performed but the scholars should be careful since the bilateral mechanism is applied.

The first part is about the usage of Square Multiple Correlation (R^2) that has been carry on this research. In basically, R^2 is used to let the researcher identify whether their research is adequate or not for their research. However, the authors suggest that this method is not only limited to justify the structural model but also helps the scholars to identify which one of the independent variable is importance and performance regardless of statistical assumption. This approach is justify since the most importance and performance factor namely Benefit construct is constantly performed for the subsequent analysis.

Afterwards, the authors performed three approaches to carry on the multi-group analysis on the basis of formula and step by step provided. Based on the findings presented, two approaches namely permutation test and non-parametric test suggest the similar result, in particular, gender groups do not influences the causal effect between four independent variable on Motivation (endogenous construct). Nevertheless, non-parametric confidence set interval reveal that the Challenge factor is the only one factor has significant influenced by gender group on Motivation, in a while, other factors provide the same result.

RECOMMENDATION

This subtopic is exist to improve the limitation that has been faced by authors to accomplish the research work. The first things is about the sample size used should be enlarged for the future research in order to ensure the findings more accurate and meaningful. This is because the sample size can be a main problem that causes the approach present different result. The second things are about the moderator variable applied. In this case, the author stress on gender group to be a moderator variable based on the literature review has a potential to moderates the influence between exogenous and endogenous construct. However, almost approaches suggest that this gender group do not have potential to influence the capability of Motivation. Thus, it might be a good reason for authors to propose other categorical or continuous factor to support our theoretical in the next research.

The third part, the authors suggest this approaches should be employ in SmartPLS 2.0 since the practice of multi-group analysis has become a main research for academicians to extend their research. The fourth part, PLS-SEM is more interesting once the developers also provide the approaches for more than two groups in multi-group analysis. The last part is about the assessment for measurement and structural model should be performed. This is because some researcher interest to justify their work based on assessment in order to justify their work to readers.

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