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 becoming more prominentas an alternative toCovariance Based Structural Equation Modeling (CB-SEM) because the technique employ is much comfortable. Thereby, this research paper intend to present guide on how to carry on the Partial Least Square based on Multi-Group Analysis (PLS-MGA) using categorical variable. In particular, the discussion of PLS-MGAcomprises of three approaches namely permutation test, non-parametric test, and non-parametric confidence set interval. The three approaches are established as non-parametric test in which no statistical assumption of normality is assumed. Thus,this paper is aimed atdetermining which approach is more appropriateto apply so as to present the guide for readers. Moreover, the practice of Square Multiple Correlation (R^2) also has been sustained 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 moderated 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. This paper is an attempt to show how the three approaches namely permutation test, non-parametric test, and non-parametric confidence set interval is achieved.

Keywords: Partial Least Square based on Multi-Group Analysis (PLS-MGA), permutation test, non-parametric test, non-parametric confidence set interval test, importance and performance.

Introduction to CB-SEM

Recently, majority of the researchers and scholars are interesting implementing 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 (Afthanorhan, 2014). Thus, the prevalence of this particular method has become a choice for many researchers especially in social science discipline (Hairet., al 2013).

In particular, the strength of this method can ascertain the scholar to execute their analysis with less complicated and cumbersome. Henseler, Eingle&Sinkovics (2009) established SmartPls 2.0 to carry on the VB-SEM approach and several articles has been published by many prominent researchers such as(Sarstedt, 2009;Ringle, 2005; Hair et. al, 2010; Chin&Dibbern, 2010). According to Afthanorhan (2014), VB-SEM can be equatedwith Partial Least Square Structural Equation Modeling (PLS-SEM) that was introduced by Wold (1982) and being enhance to improve the capability of PLS-SEM by (Lohmoller, 1989). However, PLS-SEM is less popular compare to CB-SEM since there still a lot or argument to defend PLS-SEM especially for the assessment of fitness (Afthanorhan, 2013).

Consequently, most researchers such as (Ringle et. al, 2011; Henseler, 2009; Hair et. al 2010) modified this method to become more meaningful in order overcome the limitation of CB-SEM. Previously, CB-SEM is perceived to be the best method for the research usingquantitative analysis since the method applied provide more assessment and obey the statistical assumption provided. In some other, researchers often compute the mean of items for each variable to help them analyze their research rather than to dealwith each items in line the statistical assumption given.

In particular, CB-SEM has two types of model comprises of measurement model and structural modelregarding to our objective of this research. Measurement model is commonly used for Confirmatory Factor Analysis (CFA) to confirm which items or indicator in each construct should be retained for the subsequent steps which is structural model (Afthanorhan, 2014). The researchers assess the fitness of measurement model using some established bench mark. According to Henseleret. al (2012), the fitness of model provide a meaningful fitness 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 et. al, 2013). The procedure for this method is manly for evaluation process rather than the prediction process. In fact, the scholarsare more interested in carrying out 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 withoutemphasis on non-normal data. In generals, CB-SEM needs at least 100 sample size to attain a meaningful findings (Lowry &Gaskin, 2014). Otherwise, the result suggested would become ambiguities and of course affect the prediction process (Afthanorhan, 2014).Fitness of measurement model and sample size issuesbecome wider and restricted for scholar to investigate their analysis more profound.

Introduction to PLS-SEM

Once the scholar established the limitation of CB-SEM in some circumstances, PLS-SEM began capture an attention among scholar to settle their problem. 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 insufficientfitness to provide a better assessment for measurement model, PLS-SEM will be suitable to solve that kind of problems. Indeed, PLS-SEM 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 couldplays an important role to provide a better findings (Ringle et. al 2011). 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 Hairet. al (2013), PLS-SEM and CB-SEM were supposed to be complementing each other rather than to differentiate each approach.

Moreover, PLS-SEM is more comprehensive to be used once the scholars and practitioners failed to satisfy the statistical assumption of normality. 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, 2011). 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 (2011), 5,000 samples are needed to obtain the best result. In other words, PLS-SEM is not the kind of method to assume for each model which 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 isusedfor 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 (Razali&Wah, Y.B, 2011). Indeed, t-test can negatethe 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.

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 researchis more meaningful and better understanding to ascertain howmanagementmakes a decision in terms of values of their research.

PLS-SEM has become increasingly preferred especially when it comes to 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 to handle for formative measurement model 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 (Henseleret., al, 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.

Quantitative research technique, most of the researchers interest to advance their research pertainingon how 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 the 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, Marcolin&Newsted, 2003), non-parametric test (Henseler, 2012), parametric test for equal variances (Henseler, 2012;Afthanorhan, 2014, Kock, 2011), parametric test for unequal variances (Kock, 2011; Afthanorhan, 2014), and Henseler test (Sarstedt&Henseler, 2011). However, the aim of this research paper to guide the readers on how to generate the permutationtest 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 constructnamely Motivation. According to Afthanorhan, Nazim, & Ahmad (2014), exogenous construct namely Benefit, Barrier, Challenge and Government support related on Motivation. Therefore, this study was implemented using three approaches. Repeatedly, all of these construct established by previous literature review, in particular, the study is aimed atdetermining the youth perception towards volunteerism program. The Figure 1 shows the theoretical framework as follows:

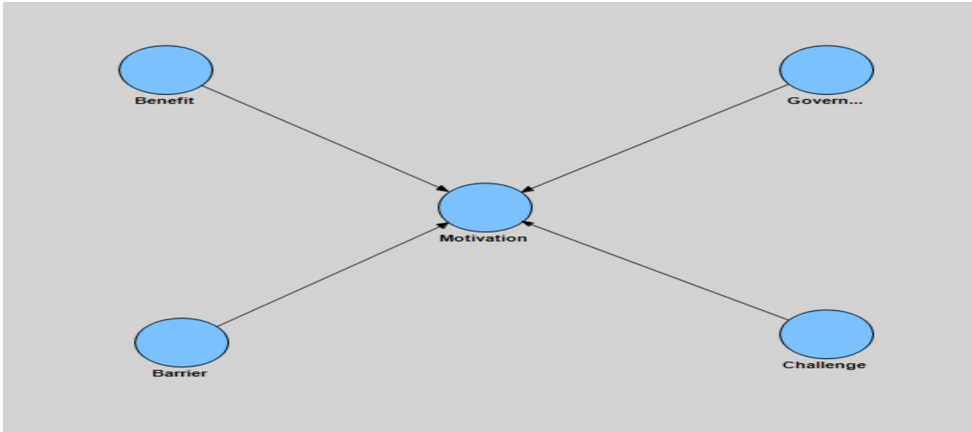


Figure 1: Theoretical Framework

Parametric Test for Equal and Unequal Variances

Parametric test is basically for the normal data and the findings will become imprecise if the scholar follow the assumption stipulated (Afthanorhan, 2014). This aforementioned approach was initially by Keilet., al (2000) and by Chin, Marcolin and Newsted (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. 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 Afthanorhan (2014), 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. 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 et.al, pg.144, 1988).

Afthanorhan (2014) stated that several steps to guide the scholars undertake their research 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 demonstrated with the illustration of formula and figures.

Permutation Approach

In this case, the paper address on the permutation approach. Permutation test is 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. 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 selected should be counted. Besides, Ringleet. al (2011) 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 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:

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

Non-Parametric Approach

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 Henseleret. 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 (AldasManzano, 2012):

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

Where:

X = 1 x > 0
X = 0 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.

Non-Parametric Confidence Set Approach

Sarstedtet. al (2011) proposed the confidence set approach 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& Young (2003) use this particular approach to carry on their research. However, Efron.B(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 (2012) suggests to use at least 5,000 bootstrap samples would require drawing more than 25 x 10^6 bootstrap samples.

FINDINGS

In this subtopic, the author 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.

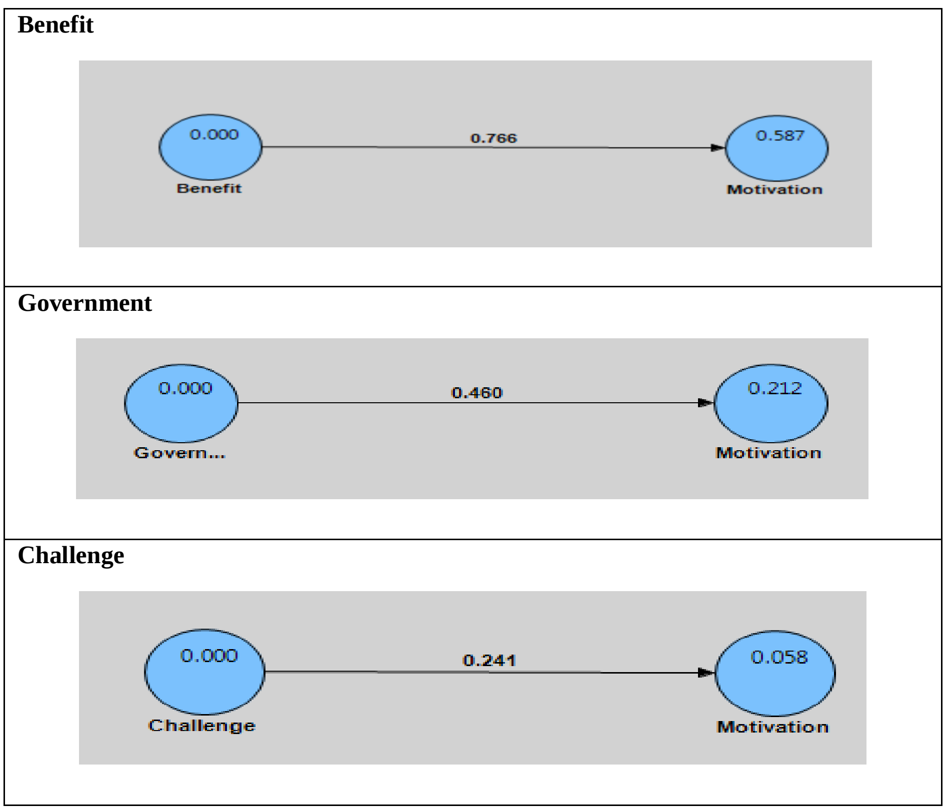
In other words, the higher of the square multiple correlationsindicated asthebetter performance. In addition, the importance of each constructs can be indicating based on the causal effect produced between exogenous and endogenous constructs. All of these construct had been executed with the same skills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

Based on the result presented in Figure 1, Benefit construct is identified as the most importance and performancefactor since the causal effect and square multiple correlationsobtained 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 correlationsis important to help the management make the decision to ensure whether each chosen factor is appropriate to further the studies. To date, all 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)



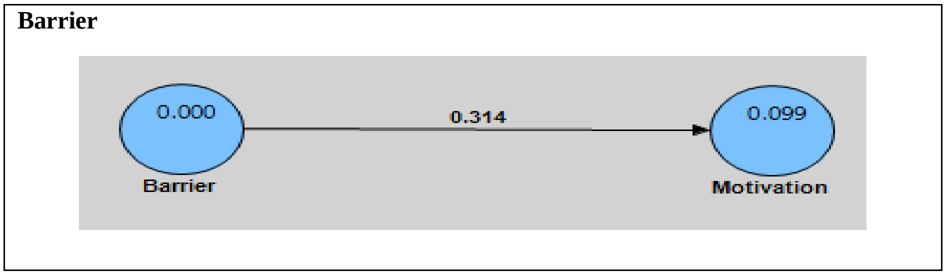


Figure 1: Square Multiple Correlation

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 research area 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 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.

Table 1: Full Model of Structural Modeling

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***

Firstly, the author carries on permutation to multi-group analysis followed by other approaches. All findings related on this approaches are presented in Table 2:

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

310

Table 2: Findings of Non-Parametric Test

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 -> Motivation	0.124517	0.1197	0.127794	0.872206

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)

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

Table 2 is not only present the result 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 Kittaneh, Berglund and Wold (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 (Kittaneh et. al., 2005).

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 suggested 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:

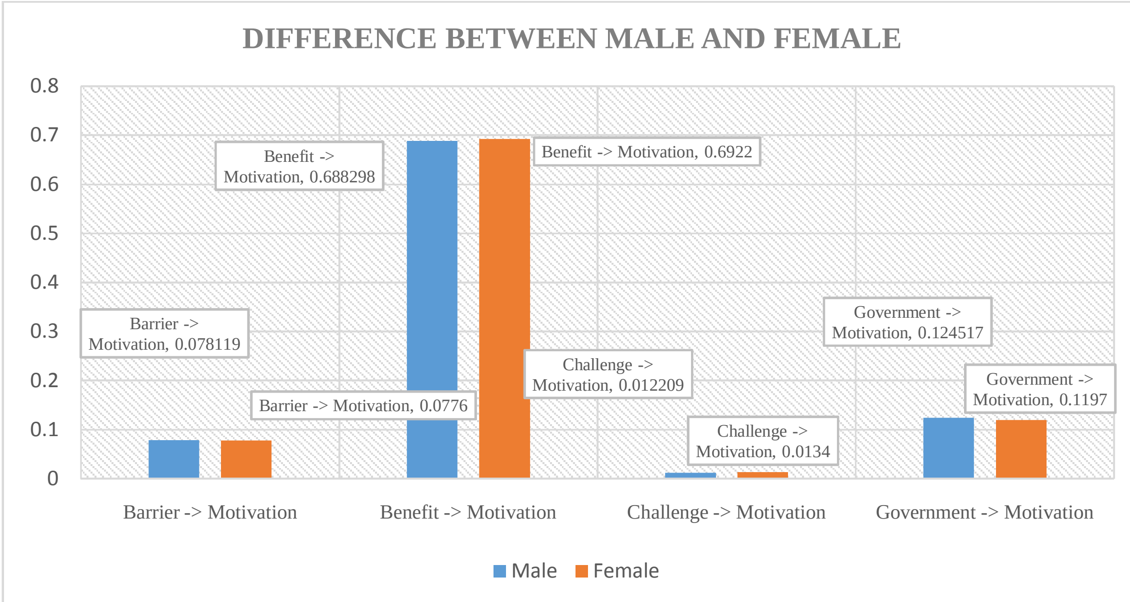


Figure 2: Difference between Male and Female

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:

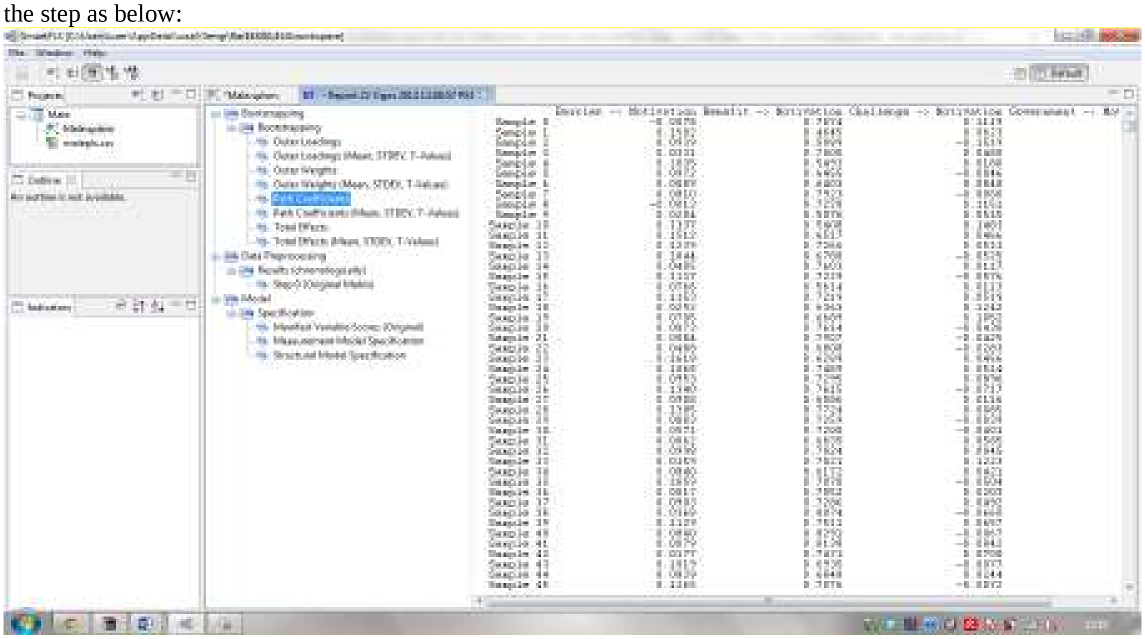


Figure 3: Male

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.

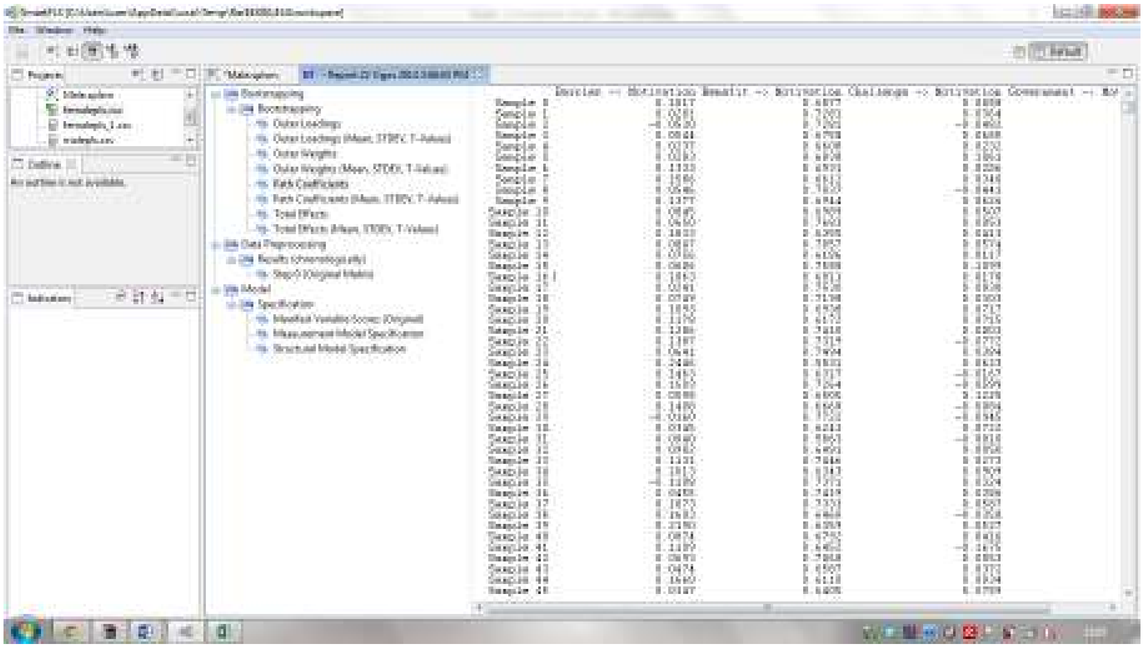


Figure 4: Female (Bootstrap)

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:

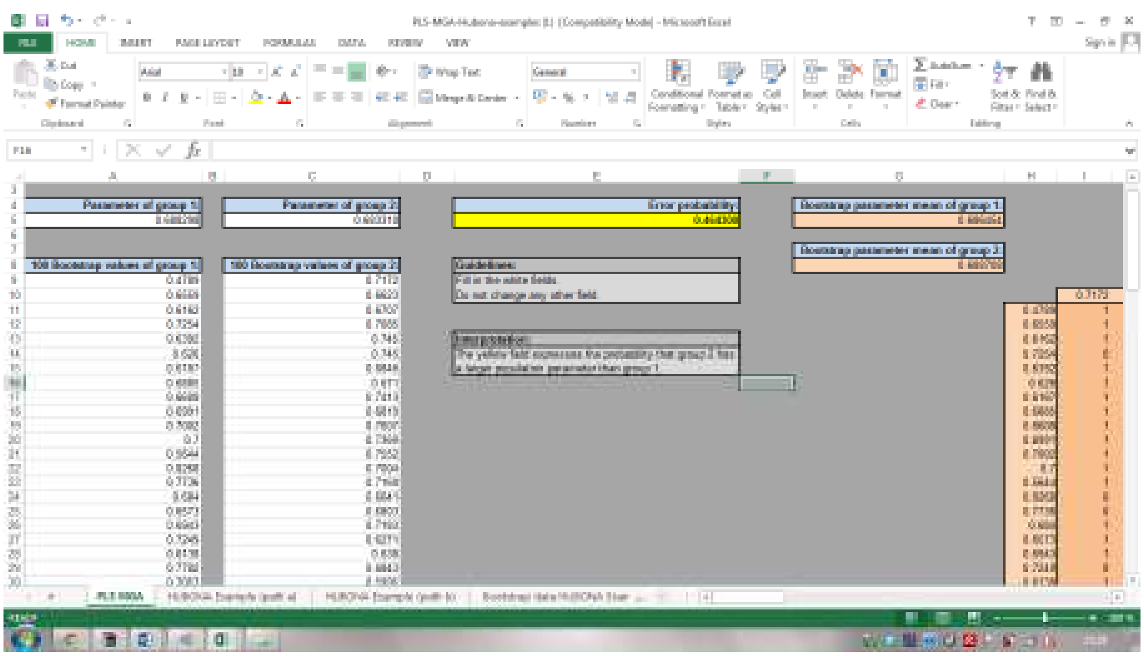


Figure 5: Non-Parametric Test

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 carries 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 as 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 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.

Previously, the authors had demonstrated the guidelines of multi-group analysis using z-test. However, z-test have limited since the normality assumption should be meet. If not, the result obtained is meaningless since the fail to achieve the requirement of z-test.

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 researchis to improve the limitation that often face 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.

REFERENCES

Afthanorhan, A., Ahmad, S., & Safee, S. (2014). *Advances in Natural and Applied Sciences,8(8)*. 108-115.

Afthanorhan, A., Nazim, A., & Ahmad, S. A Parametric Approach to Partial Least Square Structural Equation Modeling of Multigroup Analysis (PLS-MGA). *International Journal of Economic, Commerce, and Management. 2(10)*. 1-15.

Afthanorhan, W. M. A. B. W. (2014). Hierarchical Component Using Reflective-Formative Measurement Model In Partial Least Square Structural Equation Modeling (PLS-SEM). *International Journal of Mathematics and Statistics Invention, 2 (2)*, 55-71.

Afthanorhan, W. M. A. B. W., & Ahmad, S. Path Analysis In Covariance-Based Structural Equation Modeling with Amos 18.0. *European Journal of Business and Social Sciences. 3(2)*. 59-68.

Afthanorhan, W. M. A. B. W., Ahmad, S., & Mamat, I. (2014). Pooled Confirmatory Factor Analysis (PCFA) Using Structural Equation Modeling on Volunteerism Program: A Step by Step Approach. *International Journal of Asian Social Science*, *4*(5), 642-653.

Afthanorhan, W. M. A. W. (2014). Improving Energy Conservation using Six Sigma Methodology at Faculty of Computer and Mathematical Sciences (FSKM), universiti teknologi mara (UiTM), SHAH ALAM. *Asian Journal of Economic Modeling, 2 (2), 52-68.*

Ahmad, S., & Afthanorhan, W. M. A. B. W. (2014). The Importance-Performance Matrix Analysis in Partial Least Square Structural Equation Modeling (PLS-SEM) With Smartpls 2.0 M3. *International Journal of Mathematics Research*, *3*(1), 1-14.

Aldás-Manzano, J. (2012) Partial Least Squares Path Modelling in Marketing and Management Research: an Annotated Application.

Byrne, B. M. (2013). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. Routledge.

Chin, W. W., & Dibbern, J. (2010). An introduction to a permutation based procedure for multi-group PLS analysis: Results of tests of differences on simulated data and a cross cultural analysis of the sourcing of information system services between Germany and the USA. In *Handbook of partial least squares* (pp. 171-193). Springer Berlin Heidelberg.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information systems research*, *14*(2), 189-217.

Davison, A. C., Hinkley, D. V., & Young, G. A. (2003). Recent developments in bootstrap methodology. *Statistical Science*, 141-157.

Deepmala and A. K. Das, On Solvability for Certain Functional Equations Arising in Dynamic Programming, Springer proceeding of 2nd International Conference on Mathematics and Computing (ICMC 2015), during 05-10 Jan 2015, at Haldia Institute of Technology, Haldia-721657, India

Domínguez-Manzano, J., Olmo-Ruiz, C., Bautista-Gallego, J., Arroyo-López, F. N., Garrido-Fernández, A., & Jiménez-Díaz, R. (2012). Biofilm formation on abiotic and biotic surfaces during

Spanish style green table olive fermentation.*International journal of food microbiology*, *157*(2), 230-238.

Edgington, E.S. 1987. Randomization tests. Marcel Dekker,New York, NY.

Efron, B. (1981). Nonparametric estimates of standard error: the jackknife, the bootstrap and other methods. *Biometrika*, *68*(3), 589-599.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2013). *A primer on partial least squares structural equation modeling (PLS-SEM)*. SAGE Publications, Incorporated.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *The Journal of Marketing Theory and Practice*, *19*(2), 139-152.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414-433.

Hair, Joseph F., William C. Black, Barry J. Babin, and Rolph E. Anderson (2010), Multivariate Data Analysis, Englewood Cliffs, NJ: Prentice Hall.

Henseler, J. (2012). PLS-MGA: A non-parametric approach to partial least squares-based multi-group analysis. In *Challenges at the interface of data analysis, computer science, and optimization* (pp. 495-501). Springer Berlin Heidelberg.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2012). 12 Using partial least squares path modeling in advertising research: basic concepts and recent issues. *Handbook of research on international advertising*, 252.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in international marketing*, *20*, 277-319.

Keil, M., Tan, B. C., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *Mis Quarterly*, 299-325.

Kettaneh, N., Berglund, A., & Wold, S. (2005). PCA and PLS with very large data sets. *Computational Statistics & Data Analysis*, *48*(1), 69-85.

Kock, N. (2011). Using WarpPLS in e-collaboration studies: Mediating effects, control and second order variables, and algorithm choices. *International Journal of e-Collaboration (IJeC)*, *7*(3), 1-13.

Lohmöller, J. B. (1989). *Latent variable path modeling with partial least squares*(p. 130). Heidelberg: Physica-Verlag.

Lowry, P. B., & Gaskin, J. A. M. E. S. (2014). Partial Least Squares (PLS) Structural Equation Modeling (SEM) for Building and Testing Behavioral Causal Theory: When to Choose It and How to Use It. *Professional Communication, IEEE Transactions on*, *57*(2), 123-146.

Ott, W., Thomas, J., Mage, D., & Wallace, L. (1988). Validation of the simulation of human activity and pollutant exposure (SHAPE) model using paired days from the Denver, CO, carbon monoxide field study. *Atmospheric Environment (1967)*, *22*(10), 2101-2113.

Razali, N. M., & Wah, Y. B. (2011). Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests. *Journal of Statistical Modeling and Analytics*, *2*(1), 21-33.

Ringle, C. M., Sarstedt, M., & Zimmermann, L. (2011). Customer satisfaction with commercial airlines: The role of perceived safety and purpose of travel.*The Journal of Marketing Theory and Practice*, *19*(4), 459-472.

Ringle, C. M., Wende, S., & Will, A. (2005). SmartPLS 2.0 (beta).

Sarstedt, M., Becker, J. M., Ringle, C. M., & Schwaiger, M. (2011). Uncovering and treating unobserved heterogeneity with FIMIX-PLS: Which model selection criterion provides an appropriate number of segments?. *Schmalenbach Business Review*, *63*, 34-62.

Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results.*Advances in International Marketing*, *22*, 195-218.

Sarstedt, M., Ringle, C. M., Henseler, J., & Hair, J. F. (2014). On the emancipation of PLS-SEM: A commentary on Rigdon (2012). *Long Range Planning*, *47*(3), 154-160.

Sarstedt, M., Schwaiger, M., & Ringle, C. M. (2009). Do we fully understand the critical success factors of customer satisfaction with industrial goods?-extending Festge and Schwaiger's model to account for unobserved heterogeneity. *Journal of Business Market Management*, *3*(3), 185-206.

Wold, H. (1982). Soft modelling: the basic design and some extensions.*Systems under indirect observation, Part II*, 36-37.

Deepmala, A Study on Fixed Point Theorems for Nonlinear Contractions and its Applications, Ph.D. Thesis (2014), Pt. Ravishankar Shukla University, Raipur (Chhatisgarh) India – 492 010.

V.N. Mishra, Some Problems on Approximations of Functions in Banach Spaces, Ph.D. Thesis (2007), Indian Institute of Technology, Roorkee - 247 667, Uttarakhand, India.