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A PARAMETRIC APPROACH TO PARTIAL LEAST SQUARE STRUCTURAL EQUATION MODELING OF MULTIGROUP ANALYSIS (PLS-MGA)

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Abstract

Recently, Partial Least Square Structural Equation Modeling (PLS-SEM) has become pervasive among the scholar in variety of areas to examine or predict selected variables in order to achieve the goals that have been set based on the issues faced by researchers. Thus, vary of method has been performed to ascertain the researchers attain the necessity of their survey in more holistic. The main objective of this empirical works to provide a step by step approach to anyone whom interested to perform a multi-group analysis (moderating effect). In particular, the author practice the parametric approach that has been proposed by previous research using two different methods of equal and unequal variances. For this instances, five variables selected which are Benefit, Barrier, Government, Challenge and Motivation introduced to practice of these both approach. All of these variables have been tested with the existence of moderating

effect (gender variable) to identify whether of particular moderator variable has a potential to affect the impact of causal effect in PLS-SEM. Of rely on both differences methods, the PLS suggest that gender variable is not a main issue whether of improve or impairs the impact of the survey implemented.

Keywords: Partial Least Square Structural Equation Modeling, Multi-group analysis, Moderating effect, equal and unequal variances, parametric approach

INTRODUCTION

In behavioral research, multi-group analysis has been prominent among scholars to advance their statistical methodology conformity to their main objective provided. Nevertheless, researchers nowadays interest to stress their research using covariance based structural equation modeling (CB-SEM) with statistical package launched rather than partial least square structural equation modeling (PLS-SEM). In fact, PLS-SEM has a comprehensive potential to cover the loopholes of CB-SEM likely permissive to undertake the parametric and nonparametric analysis grounded on type of data attained. In CB-SEM, the scholars should be complementary the requirement and necessity at first before to undertake the subsequent step. This method is quite cumbersome since the evaluation of measurement model has become a major thrust in findings compare to our main targeted (Afthanorhan, 2014).

Unlikely of PLS-SEM interest to press on methodological of statistical analysis in order to assists scholars attained what in more need for their research (Afthanorhan, 2014). Of addressing on multi-group analysis using partial least square with SMARTPLS 2.0 M3 as a main of this research work, the author would to reveal the two types of approach namely equal and unequal variance to identify whether the continuous or discrete variables are possible to moderates the influences of exogenous on endogenous constructs (Hair et. 2013).

Both of these approaches are shift in a same route as a parametric approach in multi-group analysis (moderating effect). This particular technique has become a pervasive among scholar to provide a better understanding on the contribution of the research work. Meanwhile, the ways of the researchers to convey or present the direction of the work has become substantive.

In this research paper, the author practice four exogenous construct (Government support, Benefits, Challenge, and Barrier) imposing on one endogenous construct (Motivation).

There are several research hypotheses that have been identified through the knowledge of author to carry on the further analysis. The research hypotheses are stated as below:

H1: Government support has a causal effect on Motivation

H2: Benefit has a causal effect on Motivation

H3: Challenge has a causal effect on Motivation

H4: Barrier has a causal effect on Motivation

H5: Gender moderates the causal effect of Government support on Motivation

H6: Gender moderates the causal effect of Benefits on Motivation

H7: Gender moderates the causal effect of Challenge on Motivation

H8: Gender moderates the causal effect of Barrier on Motivation

MEASUREMENT INVARIANCE

In order to carry on the multi-group analysis, the measurement invariance approach should be carry on first to ensure this analysis should be conducted to achieve our main objective research. However, measurement invariance is rarely been used in PLS-SEM rather than CB-SEM in other statistical research due to the facts that probability to attain a less invariance in modeling is prone to CB-SEM. A less measurement invariance is emanates from the requirement of sample size is larger than PLS-SEM to judge Structural Equation Modeling (SEM) approach. In social science, this method has been substantive to apply due to the scholars enjoy to compare the selected group influences on their theoretical framework thus far. Testing for measurement invariance, that is, identify if items used in survey of material is mean the same thing across the group provided (Cheung & Rensvold, 2002). In particular, if the measurement invariance failed to be proved, the findings concerning of multi-group analysis has become ambiguous.

Thus, this testing so far is very closely related to be carrying on once the scholars be going to compare groups (multi-group analysis). There are two types of invariance that has been proposed by Little (1977) namely measurement scales, and includes configural invariances (Buss & Royce, 1975; Irvine 1969; Suzuki & Rancer, 1994), metric invariance (Horn & McArdle, 1992) and scalar metric (Steenkamp & Baumgartner, 1998). One of the criteria that should be first undertakes is the model should be measurement invariance. However, Steenkamp & Baumgartner (1998) suggest that this entails when the scholars does not have evidence to justify it. In other words, if the scholars or researchers have a proof to imply that moderator effect is restricted to which parameter, thus, does not entail group-related difference in the item loadings.

PARTIAL LEAST SQUARE MULTI-GROUP ANALYSIS (PLS-MGA)

Partial Least Square Multi-group-Analysis (PLS-MGA) can be known as moderating effect to moderates the causal effect between exogenous and endogenous constructs (Afthanorhan & Ahmad, 2014). Three approaches to multi-group analysis have been proposed within the PLS path modeling lately by infamous researchers whom expert in their fields likely parametric, nonparametric and permutation approaches. In the accordance of Keil et. al (2000), the standardized error or standardized deviation for each sample is prevailed to yield the outcome of probability value (p-value). As usual, p-value often is being used in statistical analysis to test the potential of our analysis. In other words, these values are deemed as a threshold to decide the significant of the case study applied.

In particular, these approaches entail a resampling technique (bootstrapping method) as a source in multi-group analysis to provide a standard error for each sample tested. This method generally is considered as a parametric approach since the circumstance of this behavior approach is inappropriate to be nonparametric approach (Henseler & Sarstedt, 2007). Of a main of this research to focus on parametric approach, the author claims to guide the steps for the readers to establish the parametric approach in multi-group analysis using PLS-SEM with SmartPLS 2.0 M3.

PARAMETRIC APPROACH

The parametric approach was initially been proposed by Keil (2000) and then has been modified by Chin (2003) to improve the potential of independent t-test in multi-group analysis. However, since this techniques is considered as a parametric approach, thus, the data provided should be achieve the requirement to be known as normally distributed. The data which contrary the necessity of normally distributed should be eluding since the findings will become ambiguities. Consequently, the researchers will conduct the normality test such as Kolmogorov-Smirnov, Shapiro Wilks, Liliefors correction (Mooi & Sarstedt, 2011) or other test related to identify the distribution of data. All of these data can be conducted using various statistical package such as SPSS, Eviews, Minitab, Matlab and so forth.

In CB-SEM, the researchers has been introduced to Mahalanobis Distances to determine the normality of data provided contrary of PLS-SEM, in particular, has been developed to overhaul the limitation of CB-SEM (data should be larger than 200 samples). In the accordance of Arshad et. al (2003), Shapiro Wilks test is perceived the most powerful approach for normality test especially in a small sample size composite approximately below 50. In this case, the author uses Kolmogorov Smirnov to examine the normality of the data. In the nature of statistical analysis, parametric approach can be handled once the data achieve the

requisite sample size. However, Byrne (2010) stated that the data which failed to meet the requirement assumption can be assists with the existence of resampling technique (bootstrapping method) that has been proposed by Monte Carlo (Arellano & Bond, 1991). Of stressing on the resampling technique, many eminent authors namely Mackinnon (2000), AF Hayes (2009), Byrne (2010), Kenny (1998), Afthanorhan (2014) use this aforementioned approach to perform their analysis conformity of the objective research.

On the conformity of the purpose empirical studies, the author performs equal variance and unequal variance (sattherwite test) of studentditized t-test. This method has been justified by Henseler (2007) to announce this approach has potential to play an important role as a parametric approach. Indeed, both of these approaches should be identified first once to implement to remedy the bias result. Henseler & Hair (2014) and Kock (2012) confirmed to apply of this particular method namely equal and unequal variance respectively. These authors use a different software which is SmartPls 2.0 (equal variance) and WarpPls 3.0 (unequal variance) to perform multi-group analysis. However, that's not a big matter to argue of these different approaches since both of them are classified from the same route.

Equal Variance

Equal variances studentditized t-test has been consider as parametric approach by Henseler (2007) when to apply in multi-group analysis. Usually, equal variance has been practices once the groups will be tested more than one and ta the same the sample size should be same. Otherwise, the finding will become incorrectly since contradict the assumption of statistical analysis. In addition, this particular test often assumes the analyses are normally distributed. In this case, the author had applied the Kolmogorov-Smirnov to determine the pattern of distribution whether be classify as normality or not.

These approaches just assume the raw data are normality without take into account of the evaluation for inferential analysis. The formula is presented as below:

$$t = \frac{Path_{sample\_1} - Path_{sample\_2}}{\left[\sqrt{\frac{(m-1)^2}{(m+n-2)} * S.E._{sample1}^2 + \frac{(n-1)^2}{(m+n-2)} * S.E._{sample2}^2}\right] * \left[\sqrt{\frac{1}{m} + \frac{1}{n}}\right]}$$

Path sample 1: Path coefficient sample for Group 1. In this case, the author select Male

Path sample 2: Path coefficient sample for Group 2. In this case, the author select Female

m : Total sample for Group 1; n : Total sample for Group 2

S.E : Standard error for each group selected

UNEQUAL VARIANCE

Unequal variance can be known as Sattherwite test to determine the significant of path effect when to compare groups (more than one). According to N Kock (2013), unequal variance test is appropriate to be tested once to apply multi-group analysis (modeling the moderating effect). This is perceived more relevant compare the equal variance since this test just not assumes all the data are normally distributed. Nevertheless, this test is limited in several package such as WarpPls and rarely been performed in other software. The formula is presented as below:

$$t = \frac{\beta_1 - \beta_2}{\sqrt{SE_1^2 + SE_2^2}}$$

Degree of Freedom (Chin, 2000):

$$v = \frac{\left(SE_1^2 + SE_2^2\right)^2}{\frac{SE_1^4}{m+1} + \frac{SE_2^4}{n+1}} - 2$$

B1: Path coefficient sample for Group 1. In this case, the author select Male

B2: Path coefficient sample for Group 2. In this case, the author select Female

m : Total sample for Group 1; n : Total sample for Group 2

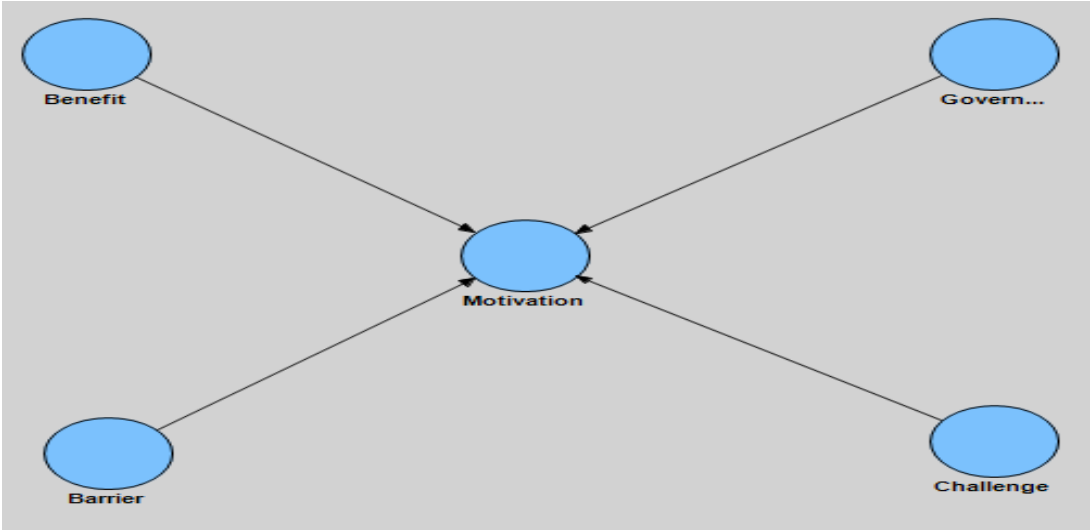
S.E : Standard error for each group selected

Theoretical Framework

The five constructs (Benefit, Barrier, Challenge, Government and Motivation, See Figure 1) are emanating from the discovering of previous literature review to carry on the multi-group analysis with SmartPLS 2.0 M3.

As aforementioned, multi-group analysis has been prominent among scholars to identify whether the selected variable (continuous or observed) has a potential to moderates the causal effect of exogenous on endogenous constructs. In this case, the moderator variable (gender) will be imposed on the effect of Benefit (Independent) on Motivation (dependent). Moderator variable (gender) should be applied based on the several assumption or previous findings to strengthen our findings is supported.

Figure 1: Theoretical Framework



In other words, this paper intend to use gender as recommended from ex-research to justify our proof in which gender is perceived to moderates the causal effect of whether of enhance or deteriorates the influences of independent on dependent variable. Moderator variable can be applied on other path but should be devoursa strong evidence to support our analysis as well as to dodge the contrary of theory in statistics. In this case, the author interest to apply moderator variable between Benefit and Motivation using parametric approach which is equal and unequal variance of t-test.

ANALYSIS & FINDINGS

In further analysis, the researchers should build their constructs based on the theoretical framework. In this case, the four exogenous construct exerting on endogenous construct. The multi-group analysis can be further once this approach achieves the requirement of partial least square namely traditional structural model. List of steps is stated as below:

1. Build of latent construct according to the theoretical framework as well as insert the indicators (items) in each latent construct. The researchers can choose either one to be hide or appear in framework
2. Execute PLS algorithm to acquire the factor loading and the path effect. Factor loading below than 0.60 should be drop since they have been consider bringing a less contribution.
3. Then, execute bootstrap to determine the t-statistics and standard error.

4. Make sure the entire requirement such as Cronbach Alpha (Nunally, 1978), Composite Reliability (Nunally & Bernstein 1994), Average Variance Extracted (Fornell & Larcker, 1982), and Discriminant Validity (Fornell, 1988, Afthanorhan et. al 2014).

Figure 2: Estimated Path Coefficients

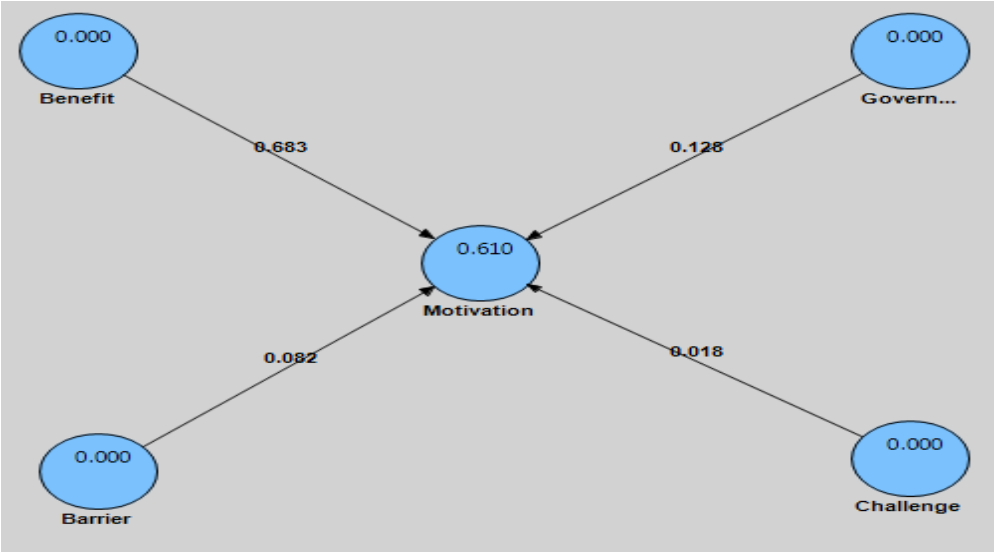


Table 1: Path Coefficients (Mean, STDEV, T-Values)

		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 1 present the path coefficient of exogenous on endogenous construct once execute PLS algorithm and bootstrap to provide the beta coefficient, sample mean, standard error and t-statistics for each causal effect. In this case, beta coefficient can be known as original sample. By inspecting through for each row in a Table 1, factor Benefits (0.683) is expected to be the highest effect on Motivation follow by Government (0.127), Barrier (0.0821) and Challenge (0.0180).In further steps, the scholars should stress on t-statistics as a guide of whether to accept or reject our research hypothesis.

H1: Barrier has a causal effect on Motivation

The finding suggests that Barrier significantly has a causal effect on Motivation. It can be perceived when the outcome of t-statistics is higher than 1.96 (P-value = 0.05). Thus, one can be conclude that the research hypothesis is supported.

H2: Benefits has a causal effect on Motivation

The finding suggests that Benefit is highly significant impact on Motivation. It can be perceived when the outcome of t-statistics is higher than 1.96 (P-value = 0.05). Thus, one can be conclude that the research hypothesis is supported.

H3: Challenge has a causal effect on Motivation

The finding suggest that Challenge is does not has significant impact on Motivation. It can be perceived when the outcome of t-statistics is below than 1.96 (P-value = 0.05). Thus, one can be conclude that the research hypothesis is not supported and totally contradict the theory of previous research.

H4: Government has a causal effect on Motivation

The finding suggests that Government significantly has a causal effect on Motivation. It can be perceived when the outcome of t-statistics is higher than 1.96 (P-value = 0.05). Thus, one can be conclude that the research hypothesis is supported.

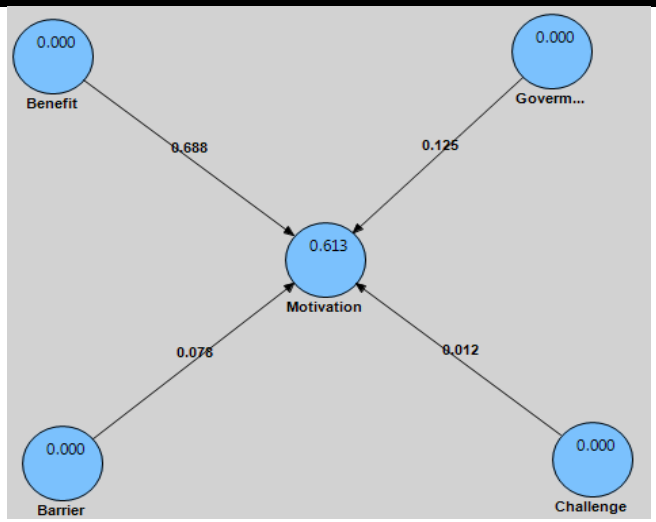
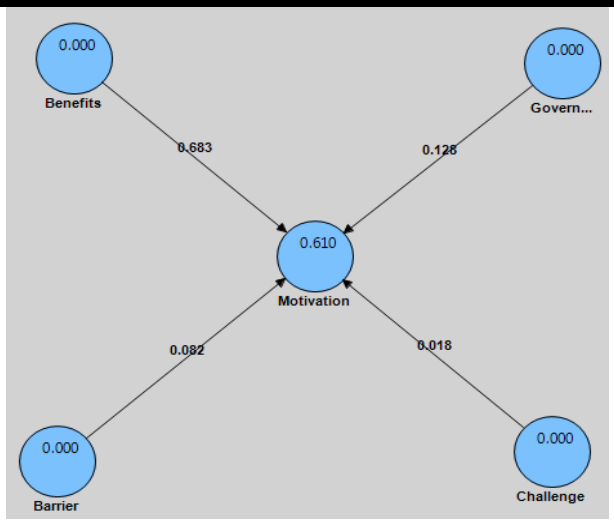
MULTI-GROUP ANALYSIS (MODELING THE MODERATING VARIABLE)
EQUAL VARIANCE APPROACH

Now, the multi-group analyses were conducted to each causal path that has been provided in theoretical framework. The procedure to implement of this approach is quite simple rather than CB-SEM. The first part makes sure the researcher build the construct based on theoretical framework in order to prevent contradict of research hypothesis. List of steps is stated as below:

1. Database is split in two groups according the moderator variable. In this case, the author split the sample size for gender group.
2. The model is executed twice, one for each database, and the beta parameter is estimated in groups as well as the t-values, standard error and standard deviation. All of these result is existence in a same table
3. Outcome for t-statistics can be appears once the research executes the resampling technique (bootstrapping).

4. If B1 and B2 are the estimated coefficient, SE1 and SE2 are their standard error, whilst m and n is total sample size for each group selected.
5. The following of t-statistics is built to test the null hypothesis (a family pairwise error rate) that both parameter are the same

Table 2: Male and Female (Moderating Variable)

Male	Female
	

Benefit

B1 = 0.688298 B2 = 0.683311

SE1 = 0.064688 SE2 = 0.047275

M = 159 N = 293 t-value (Male) = 10.640206 t- value (Female) = 14.453983

Government

B1 = 0.124517 B2 = 0.127794

SE1 = 0.061750 SE2 = 0.044570

M = 159 N = 293 t-value (Male) = 2.016464 t- value (Female) = 2.867268

Challenge

B1 = 0.012209 B2 = 0.017979

SE1 = 0.054873 SE2 = 0.037983

M = 159 N = 293 t-value (Male) = 0.222503 t- value (Female) = 0.473355

Barrier

B1 = 0.078119 B2 = 0.082066

SE1 = 0.052801 SE2 = 0.037980

M = 159 N = 293 t-value (Male) = 1.479489 t- value (Female) = 2.160795

POOLED STANDARD ERROR METHOD (EQUAL VARIANCE)

Benefits

$$t=\frac{0.688298-0.683311}{\left[\sqrt{\frac{(159-1)^2}{(159+293-2)}}*(0.064688)^2+\sqrt{\frac{(293-1)^2}{(159+293-2)}}*(0.047275)^2\right]*\left[\sqrt{\frac{1}{159}+\frac{1}{293}}\right]}$$

t = 0.063P-value = 0.950 **Not significant different** since t-statistics is lower than 1.96.

Government

$$t=\frac{0.124517-0.127794}{\left[\sqrt{\frac{(159-1)^2}{(159+293-2)}}*(0.061750)^2+\sqrt{\frac{(293-1)^2}{(159+293-2)}}*(0.044570)^2\right]*\left[\sqrt{\frac{1}{159}+\frac{1}{293}}\right]}$$

t = 0.043 P-Value = 0.965 **Not significant different** since t-statistics is lower than 1.96.

Challenge

$$t=\frac{0.012209-0.017979}{\left[\sqrt{\frac{(159-1)^2}{(159+293-2)}}*(0.054873)^2+\sqrt{\frac{(293-1)^2}{(159+293-2)}}*(0.037983)^2\right]*\left[\sqrt{\frac{1}{159}+\frac{1}{293}}\right]}$$

t = 0.088 P-value = 0.930 **Not significant different** since t-statistics is lower than 1.96.

Barrier

$$t=\frac{0.078119-0.082066}{\left[\sqrt{\frac{(159-1)^2}{(159+293-2)}}*(0.052801)^2+\sqrt{\frac{(293-1)^2}{(159+293-2)}}*(0.037980)^2\right]*\left[\sqrt{\frac{1}{159}+\frac{1}{293}}\right]}$$

t = 0.061 P-value = 0.951 **Not significant different** since t-statistics is lower than 1.96.

In this instance, equal variances approach is employ in multi-group analysis and the findings suggest that the moderator effect (gender) do not have a significant impact to moderates the causal effect of Benefit, Government, Challenge and Barrier on Motivation. Thus, one can be conclude that the gender (moderator variable) is not a catalyst to affect Motivation.

For P-Value, we can use excel spreadsheet to attain the probability value. First, calculate the total of sample size that represent of degree of freedom. In this case, (159+293)-2 = 450.

In excel spreadsheet, write as below:

DISTR.T (t value; degree of freedom; number of tails) = p-value

MULTI-GROUP ANALYSIS PARAMETRIC APPROACH (UNEQUAL VARIANCE)

The procedure for unequal variance approach is similar to the previous of equal variance approach. Researchers deserve to choose either one of the approach that looks comfort for them because both of these approach will benefited at the same outcome. The next step is to present the calculation of unequal variances in multi-group analysis.

SATTHERWITE METHOD (UNEQUAL VARIANCE)

Benefit

$$t = \frac{0.688298 - 0.683311}{\sqrt{(0.064688)(0.064688)+(0.047275)(0.47275)}}$$

$$v = \frac{(0.064688^2 + 0.047275^2)^2}{\frac{0.064688^4}{159+1}+\frac{0.047275^4}{293+1}}$$

t = 0.0622 P-value = 0.9504 **Not significant different** since t-statistics is lower than 1.96.

Government

$$t = \frac{0.124517 - 0.127794}{\sqrt{(0.061750)(0.061750)+(0.044570)(0.044570)}}$$

$$v = \frac{(0.061750^2 + 0.044570^2)^2}{\frac{0.061750^4}{159+1}+\frac{0.044570^4}{293+1}}$$

t = 0.0434 P-Value = 0.9657 **Not significant different** since t-statistics is lower than 1.96.

Challenge

$$t = \frac{0.012209 - 0.017979}{\sqrt{(0.054873)(0.054873)+(0.037983)(0.037983)}}$$

$$v = \frac{(0.054873^2 + 0.037983^2)^2}{\frac{0.054873^4}{159+1}+\frac{0.037983^4}{293+1}}$$

t = 0.0865 P-Value = 0.9311 **Not significant different** since t-statistics is lower than 1.96.

Barrier

$$t = \frac{0.078119 - 0.082066}{\sqrt{(0.052801)(0.052801) + (0.037980)(0.037980)}}$$

$$v = \frac{(0.052801^2 + 0.037980^2)^2}{\frac{0.052801^4}{159+1} + \frac{0.037980^4}{293+1}}$$

t = 0.0607 P-value = 0.9516 **Not significant different** since t-statistics is lower than 1.96.

In this instance, unequal variances approach is employ in multi-group analysis and the findings suggest that the moderator effect (gender) do not have a significant impact to moderates the causal effect of Benefit, Government, Challenge and Barrier on Motivation same as previous approach. In this instances, *v*is indicate as a total of sample size that will be apply in excel spreadsheet for calculation of probability value.

CONCLUSION AND RECOMMENDATIONS

On the use of equal and unequal parametric approach in multi-group analysis have justify that these approaches contribute the same outcome. This can be perceived when the findings reveals that moderator variable (gender) do not has a significant impact to moderates the causal effect of exogenous path (Benefits, Barrier, Government and Challenge) on endogenous path (Motivation). All of these path are totally contradict the research hypothesis to proclaim that these moderator effect is might be affect the causal effect.

On the other hands, the author also had addressed the traditional method of which namely partial least square path modeling (PLS-PM) to determine the significant impact between exogenous and endogenous constructs. In this case, one out of four exogenous construct namely Challenge factor is expected do not has a significant impact on Motivation.

The strength of this research paper is the author had success to prove that either one of these approach can be applied in multi-group analysis. Thus, the scholars deserve to choose based on their comfort to deal the instances of this approach. However, this method is only limited for the parametric probability (normality distribution) of which contrary the main purpose of partial least square to provide the analysis for non-parametric probability.

Thus, the author suggests that the non-parametric approach should be considered for the further analysis in order to provide the analysis conformity of the aimed partial least square. Once this limitation has been curbed, the findings of the research paper will become more valuable for the next generation.

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