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. This research paper intend to presents guide on how to carry out the Partial Least Square to Multi-Group Analysis (PLS-MGA) by 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 tests 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. Henseler et.al (2012) established SmartPls 2.0 to carry on the VB-SEM approach and several articles has been published by many prominent researchers such as Sarstedt, 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

Comment [A1]: Line 10 Is becoming more prominent as an alternative to ….

Comment [A2]:

Comment [A3]: Delete is become ,,,,

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Comment [A5]: Line 11 delete due to the technique replace with because the technique employ by using PLS-SEM is much comfortable.

Comment [A6]: Line 12 delete to and replace with based on

Comment [A7]: Remove is comprised replace with comprises

Comment [A8]:

Comment [A9]: Line 15, delete replace with The three approaches are established as non-parametric test in which no statistical assumption of normality is assumed.

Comment [A10]: Line 16 , replace with This paper is aimed at determining which approach is much comfortable to apply ….

Comment [A11]: Line 18 delete promoted replace with sustained

Comment [A12]: Line 21 replace with moderated

Comment [A13]: Strength can be extended …

Comment [A14]: Line 24-27 The key ... [1]

Comment [A15]: There is need for citation.

Comment [A16]: Line 32 for many res ... [2]

Comment [A17]: Line 34 by the resear ... [3]

Comment [A18]: This Author has no ... [4]

Comment [A19]: Line 37 wrong citatio ... [5]

Comment [A20]: Line 37 Can be equated to

Comment [A21]: Line 38, That was

Comment [A22]: Line 39 and has been

Comment [A23]: Line 39 replace by ... [6]

Comment [A24]: Line 40 popular com ... [7]

Comment [A25]: Line 40 delete In that time

Comment [A26]: Line 41 citation

Comment [A27]: Line 44, citation is needed

Comment [A28]: Line 42, replace by ... [8]

Comment [A29]: Line 42 , Prior resear ... [9]

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each variable to help the analyze their research rather than to deal for each items in line with the statistical assumption given.

In particular, CB-SEM have two types of model whereby measurement model and structural model regarding to the objective of this research. Basically, measurement model is commonly used for Confirmatory Factor Analysis (CFA) to confirm which items in each constructs 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 using the parametric distribution. The parametric is considered for normal data solely without emphasized 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 limitations of CB-SEM in some circumstances, PLS-SEM began to capture attention among scholar to settle their problem faced. PLS-SEM is used to focus on variance that has been encapture 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 fitness indices that can suggests the Confirmatory Factor Analysis (CFA) due to restriction for incremental fitness.

Thus, some of the researchers suggested that the CB-SEM and PLS-SEM were play an important role to provide a better findings. In some research papers, the CB-SEM is 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 (Ringleet.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 is implementing for the large sample size but since the presentof bootstrapping technique in PLS-SEM is quite significant to convince the efficiency of t-test

Comment [A36]: with

Comment [A37]: line 50, remove and replace with comprises of

Comment [A38]: replace with the researchers' assess the fitness of measurement model using some established bench mark.

Comment [A39]: Not in reference, it should be Hair et al.(2012)

Comment [A40]: Line 58 replace with (Hair et al.,2012)

Comment [A41]: Line 59, Are more interested in carrying out their research …

Comment [A42]: Line 62 citation is needed.

Comment [A43]: Line 67 replace with established

Comment [A44]: Line 67 replace with established

Comment [A45]: Line 68, remove

Comment [A46]: Line 70 add respondants

Comment [A47]: remove

Comment [A48]: delete and replace could

Comment [A49]: line 74 citation is required

Comment [A50]: Hair et al. (2012)

Comment [A51]: Of normality.

Comment [A52]: Line 85 citation not in reference section.

Comment [A53]: Line 87 not in ref. section

Comment [A54]: Not a single author,

Comment [A55]: Change to is used

Comment [A56]: Line 95 not in reference section

Comment [A57]: Replace with negate

fortestingsignificantlevel.Thus,thescholarswhoimplementPLS-SEMrelyont-testtocapturethe significantlevelforeachmodeldesigned.

Inseekofenjoymentto PLS-SEM,avarymethodhavebeenproposedbasedontheirresearch work.Thishabitisnotinevitablyinsocialscience,management andmarketingdisciplinesespecially fortheacademicians.The pathanalysisofPLS-SEMcouldbeextendingtobemoreimportance once thispackage offerstheImportance-PerformanceMatrix Analysis (IPMA) toidentifytheimportance andperformanceforeachfactor.Consequently,theseresearchis moremeaningfulandbetterfocus on howmanagerialmakedecisionintermsofvaluesoftheirresearch.

PLS-SEM has become increasingly preferred especially when it comes for the analysis that involveahigherconstructs.Inparticular,PLS-SEMalsooffersauser-friendlytodevelopastructural model that has potential to become as reflective or formative constructs. In fact, CB-SEM also managedtoobutthemechanismtobeusedisquitecumbersomeandtakestimetodoso.Thus,mostof theresearchersintendtoapplyPLS-SEMthatdistinguishtheroleof reflectiveandformativeconstructs (Afthanorhan,2014).

Besides,PLS-SEMalsointroducingtosegmentationapproachthatbasicallybeenusedamong themarketingandmanagement sectortoidentifyanumberofsegmentandtypeofexistenceforeach segment. InPLS-SEM, Finite Mixture Partial Least Square Structural Equation Modeling (FIMIX-PLS)istheonlyonesegmentation methodconstituted(Ringle,2012).Thisaforementioned methodis perceived morerelevant ratherthanResponse BasedSegmentation (REBUS-PLS). Forthecommon knowledge,CB-SEMdonotprovidethesegmentationclassesinsteadtargetedonpathanalysissolely.

Instatisticalresearch,mostoftheresearchers interest is toadvancetheirresearch with regards to distinguishingthecategorical variable(e.g.:gender,race,education,salaryandstatus)ontheirmodel. This model recognized as modeling moderation butthe method used been classify as multi-group analysis (Afthanorhan, 2014). Multi-group analysisencouraged the scholar to probe their research moreprofoundandextensiveso astocapableexpandstheirresearchinahigherlevel.Inaddition,the findingswouldbecomemoreinterestingandinclusivenessto determinewhetherofcategoricalvariable (moderatorvariable)hasapotentialtoinfluencethecausaleffect.Inthiscase,theauthorsemploythe gender(maleandfemale)tomoderatethecausaleffect.

Truly, there arefiveapproaches established todecide theprobability leveltoPartial Least Square Structural Equation Modeling Multi-Group Analysis (PLS-MGA) such as permutation test (Chin, 2003),non-parametric test(Ringle, 2014), parametric testforequal variances (Ringle, 2012; Afthanorhan,2014,N.Kock,2014),parametrictestforunequalvariances(N.Kock,2014;Afthanorhan, 2014),andHenselertest(Henseler,2010).However,theaimofthisresearchpaper istoguidethereaders togeneratethepermutationandnon-parametricapproachestoPLS-MGA.

THEORETICALFRAMEWORK

Theoretical frameworkisthemostimportant thingthatshouldbefocused oncewewantto determine the objective research. As aforementioned, the four exogenous construct are pointing outwards tooneendogenous construct. Repeatedly, allofthese construct should beestablished by literature review, in particular, the study is prevailed to determine the youth perception towards volunteerism program.Thefailedsupportingofourresearchmightproduceinaccurate. TheFigure1 showsthetheoreticalframeworkasfollows:

Comment [A58]: Line 99, citation is needed

Comment [A59]: Line 100 what do you mean

Comment [A60]: Line 105 replace with management

Comment [A61]: Line 119, replace with quantitative research technique,

Comment [A62]: Permutation test

Comment [A63]: Line 138 why ?

Comment [A64]: Replace with aimed at determining

Comment [A65]: This sentence is not clear enough

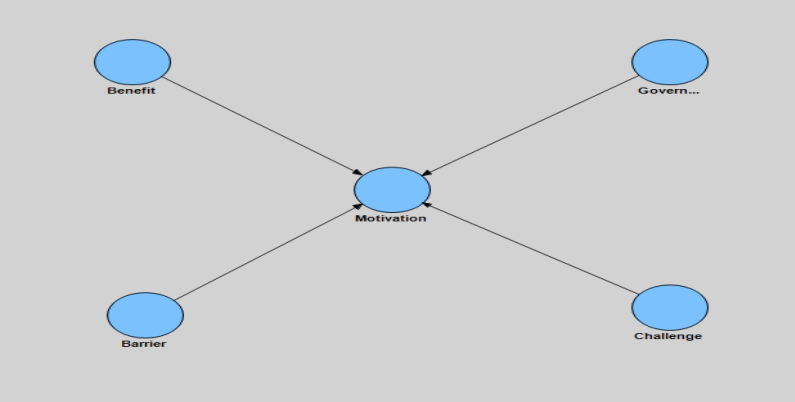

Figure1:TheoreticalFramework

ParametricTestforEqualandUnequalVariances

Parametric testisbasicallyforthenormaldataandthefindingswillbecomeimpreciseifthe scholar apply the contradict assumption (Afthanorhan, 2014). This aforementionedapproach was initiallyby Keil(2000)andthenhasbeenextendedbyChin(2003)toensuretheaccurateanalysisfor probabilitylevel.In PLS-SEM,thenormalitytestisnotprovidedsincetheappliedmethodisusefulfor variousdata.Inotherwords,theparametricandnon-parametrictestisallowedtobeconductedinorder toachievetherequiredobjectiveresearch(Afthanorhan,2014).However,theimplementation ofPLS-SEMdoesnotassumeallthedataconstitutedarenormal.

Thus, the bootstrapping technique isassists researchers gain the normal data. Inprevious research,theauthorshadpublishedtheguideforparametrictestthatcomprisedof equalandunequal variances.Theequalvarianceassumptionisimportantindeterminingwhichappropriatestatisticaltest tobeuse.Thus,thebox-plottesthadprovidedinsomepackagessuchasSPSS,MINITAB,andEviewstohelp theresearchers to identify the types of variances. According toNCSS statistical software chapter206,ifthedataarenon-normal,themodifiedLevenetestcanbea greathelpfulformanynon-normalsituations.Someresearchersrecommendagainstusingapreliminarytestonvarianceinwhich donothaveastronglysupported tostandthefindings. Thus,ifthescholars decideagainst these preliminarytest,theratioofthesamplesizes(largersamplesizeoverthesmallersamplesize)isequal toorgreaterthan1.5isconsideredasunequalvariancet-test(Ott,pg.144,1984).

Afthanorhan(2014)statedthatseveral stepstoguidethescholars undertake theirresearch. Listofstepsisstatedasbelowfortheequalunequalvariances:

1. Buildoflatentconstructaccordingtothetheoreticalframework.
2. Assignthedataaccordingtogendergroup(Male=1,Female=2)
3. Permutethestructuralmodelbasedonspecifiedgroups
4. ExecutePLSalgorithmforeachspecifiedgroups.
5. Thet-statisticsforeachgroupswillbecarryontothenextsteps
6. Calculate theprobability levelbasedontheKeil(2000)andChin(2003)formulae for equalandunequalvariancest-test.
7. P-valuelessthan0.50consideredsignificantpaths(Rejectnullhypothesis).
8. Thep-levelforbothtestsshouldbesameevencarrythedifferentofbetacoefficient.

Themainofthisresearchpapertoaddressonthepermutationandnon-parametric test.Thus, theguideofthistestwillbeilluminatewiththeillustrationofformulaandfigures.

PermutationApproach

Comment [A66]: Justification of the framework? Is this adopted or adapted

Comment [A67]: Is employed to

Comment [A68]: Line 151 by whom?

Comment [A69]: Wrong citation have to cite correctly

Comment [A70]: Line 160 wrong citation

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Comment [A72]: line 173 aim

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In this case,thepaperaddresson thepermutationapproach.Permutationtestcanbeknownas randomization test that does notrely on statistical assumption to attain the normal data. A randomization testisconductedbyenumeratingallpossiblepermutations ofthegroupswhileleaving thedatavaluesintheoriginalorder.Inthiscase,thegroupswillbetestisgendergroups(maleand female).Thedifference iscalculated foreachpermutationthatprovidedineachspecifiedgroupsand thenumberofpermutationthatresultinadifferentwitha magnitudegreaterthanorequalto theactual differenceiscounted.Thistestisfreelydistributionsincethetestisstipulatedby self-researchers. The proportionshouldbecountedbasedthenumberofpermutationstriedgivesthesignificantlevelofthe test.

According toEdgington(1987), atleast 1,000 permutation byselected should becounted. Besides,Ringleet.al(2014)suggesttopermuteby5,000permutationsincethebootstrappingtechnique willbecalculateintheslowerrate.Inthiscase,theauthoralsousesthesamescaleofRingletoprovide allthepossiblepermutation. Thestepsinpermutationarealmostthesameaspreviousapproachsince onlyhasdifferentinobtainingofprobabilitylevel.Listofstepsarestatedasbelow:

1. Buildoflatentconstructaccordingtothetheoreticalframework.
2. Assignthedataaccordingtogendergroup(Male=1,Female=2)
3. Permutethestructuralmodelbasedonspecifiedgroups
4. ExecutePLSalgorithmforeachspecifiedgroups.
5. Theoutputofpathcoefficientforeachspecifiedgroupswillbeappearindefaultreport.
6. Extractthevalueofpathcoefficient(OriginalMean)foreachpathinstructuralmodelof specifiedgroups(MaleandFemale).
7. Calculatethedifferenceofeachspecifiedgroups(e.g:$|\pi_{male}-\pi_{female}|$)
8. Calculatetheprobabilityvalue (p-level)basedonthisformulabelow:

$$\text{P-level} = \frac{. \quad !}{"\#!}$$

Non-ParametricApproach

Previously, theauthors had published one article regarding onthe parametric approach to multi-group analysis using PLS-SEM. However, themethodology used is inappropriate since the appliedmethod(PLS-SEM)isa non-parametricapproach.Thus,thepracticeofparametricapproachto multi-group analysisisquiteunfairtodeterminethesignificant ofcausaleffectwhencomparingtwo groups in structural model. Consequently, the authorsprovide non-parametric approach based on Ringleet.al(2012)proposed.

Thereareseveral stepsprovided toguidethescholarsattaintheiranalysisregarding onthe non-parametricapproachtomulti-groupanalysis:

1. Thedatabase issplitintwoaccording tothemoderating variable. Inthiscase,theauthors choosegendervariabletoassignforeachdatabase(e.g:MaleandFemale)
2. RunthePLSpathmodelingalgorithmseparatelyforeachgroup(maleandfemale)
3. The two implied parameters B1 and B2 are estimated inthose samples. Inthis 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 samplingwouldbeagreatused.
4. Usingbootstrapping,Jestimationoftheabovementionedparametersineachsample.
5. Thus,thesignificance ofthetestalpha,theprobabilitywouldbewrongifwerejectthenull hypothesisthatthepopulation parameter B2ingroup2(Female)ishighertothepopulation parameterB1ingroupone(Male)onecanbecalculatedasfollows(JoaquinManzano,2012):

Comment [A74]: remove replace with is

Comment [A75]: The sentence need improvement

Comment [A76]: Not seen in reference page

Comment [A77]: removed

Comment [A78]: not in ref. . Sarsted et al.

Comment [A79]: grammar

Comment [A80]: remove this is against academic writing

Comment [A81]: ,evidence

Comment [A82]: Not in reference page

$$\alpha = Pr(B1 > B2 | b1 < b2) = 1 - \sum_{}^{\$\%!\%\&'\%!\%\&\%\%!} ()$$

Where:

X=1 x>0
X=0 x<0
B1= ParameterofGroup1
B2= ParameterofGroup2
J=Bootstrappingestimation

Basically, thisapproach isalmostthesameasMann-Whitneytestwhichisknownoneofthenon-parametrictests.Inotherwords,~~theprobabilitythattheestimatedparameteringroup2ishigherthan~~ theestimation ofgroup1,is1-α.Henseler(2009)hadprovide aspreadsheet ofMicrosoft excelto maketheoperationaltheprocedureaccordingtohispaper.Thus,thisresearchpaperpresentsastepby step approachto non-parametric using this sheet. The nameof sheet is PLS-Hubonathat can be attaininginGoogle.

Non-ParametricConfidenceSetApproach

Sarstedtet.all(2011)proposedtheconfidencesetapproachinwhichwasinitiativebyKeilet. al (2000) to prevent the deficiencies of methodology. Afthanorhan(2014) stated that the method developby Keilet.al(2000)isusefulfornormalitydata,thus,theindependentt-testwasconducted.In accordancewiththis test,the researcherscancomparethegroupspecificbootstrapconfidenceinterval, regardlessofwhetherthedataare normallydistributedornot(Sarstedtet.al,2011).Theprocedureis as followsbelow:

1. Thedatabaseissplitintwoaccordingto themoderatingvariable.In thiscase,theauthors choosegendervariabletoassignforeachdatabase(e.g:MaleandFemale)
2. RunthePLSpathmodelingalgorithmseparatelyforeachgroup(maleandfemale)
3. Thetwoimpliedparameters B1andB2areestimatedinthosesamples.Inthiscase,the authors had159casesformaleand293forfemale.Oncetoexecute thebootstrapping technique toattain theprobability level foreach constructs instructural model, 5,000 samplingwouldbeagreatused.
4. Constructthebias–correctedinwhich95%ismostpreferred.
5. Ifthe parameterestimates forapath relationship between exogenous andendogenous constructofgroup1fallswithinthecorresponding confidenceintervalofgroup2,itcan be assumedthattherearеno significantdifferencesbetweenthegroupspecificpath coefficients. In other words, if the parameter estimate falls outside of the confidence intervalproduced,then,itcanbeassumedthattherearesignificant differences between thespecificgroups.

Davison&Hinkley(1997)isoneoftheresearcherusethisparticularapproachto carryontheir research.Efron(1981)arguethatconfidencesetapproachismisleadingoncethedataappliedis small sample size. Inorder tosustain thecapability ofPLS-SEM tocarry onthelarge data, the double bootstrapisproposedbyHenseleret. al(2009).Thedoublebootstrapmeanscomprisedofresampling technique outperformsof5,000 samples. Hair et.al(2011) suggests touse atleast 5,000 bootstrap samplewouldrequiredrawingmorethan25x10^6bootstrapsamples.

FINDINGS

In this subtopic, the authors interesttoaddress the total variation of each construct once executed separately. Inthiscase,theauthor havefourtypeofexogenous construct namelyBenefit, Government, Challenge, andBarrierandoneendogenous construct namelyMotivation. Theseentire exogenousconstructhadbeentestedonMotivationrespectively.Thisapproachcanhelpsusto identify whichoneofthefactorswouldcontributethemostvariation.

In other words, the higher the square multiple correlations would be consider, highperformance.Inaddition,theimportanceofeachconstructscanbeindicatingbasedonthecausaleffect

Comment [A83]: Wrong citation

Comment [A84]: Wrong citation

Comment [A85]: Davison, Hinkley and Young (1997)

Comment [A86]: removed

Comment [A87]: et al.

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produced betweenexogenous andendogenous constructs. Alloftheseconstruct hadbeenexecuted withthesameskillstoprovidetheresults.InTable1havepresentfourtypesoffigureswhichrepresent ofeachconstructs.

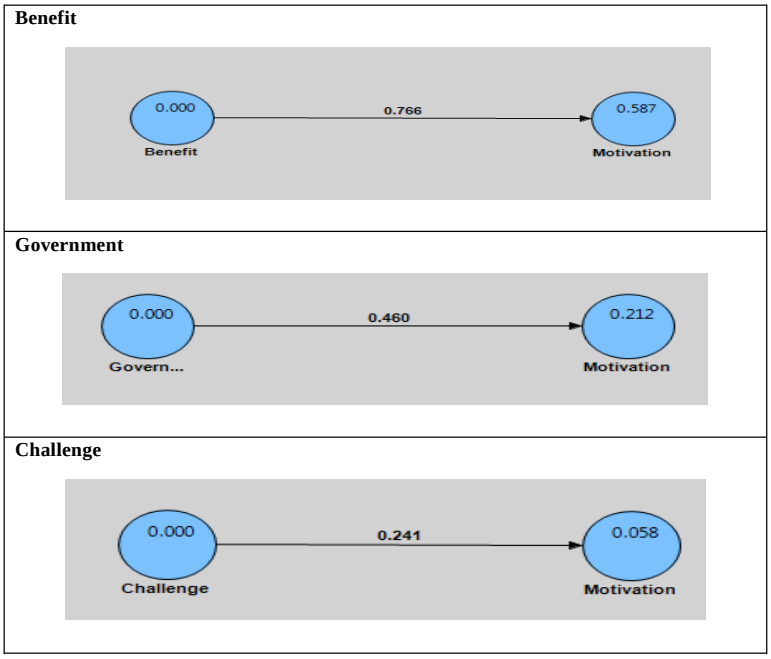
Basedontheresultpresented,The construct identify as Benefit isthemostimportanceand performance sincethecausaleffectandsquaremultiple correlations arethehighestrespectively. Of addressing the significance total variation, the interpretation should be stressed on the same thing towardsotherfactors.Inthisinstance,Challengefactorisexpectedtobethepoorestperformanceand lessimportance. Thus,thisresearchmaybeabletobeextendingtopromotethecapabilityofBenefit factorforthefutureresearch.

Comment [A90]: re structure this sentence again

In particular, square multiple correlations is important to help the managerial make the decisionto ensurewhethereachchosenfactoris appropriatetofurtherthestudies.Todate,allofthese factorsshouldberetained sincethisresearch hadagoodreasontosupportallofthisresearch even someconstructprovidelesscontribution.

However,theitemthatshouldberetainedoneachconstructshouldbeconformachieveofthe statistical assumption whichisbasicallyhigherthan0.60ofouterloadings. Moreover, thereliability and validity for each construct should be performed in order to prevent inaccurate findings. The accurate findingwouldperform themeaningful research thathaspotential tocontribute inallareas includingofsocialscience,marketing,business,managementandotherdisciplines.

SquareMultipleCorrelation(R^2)



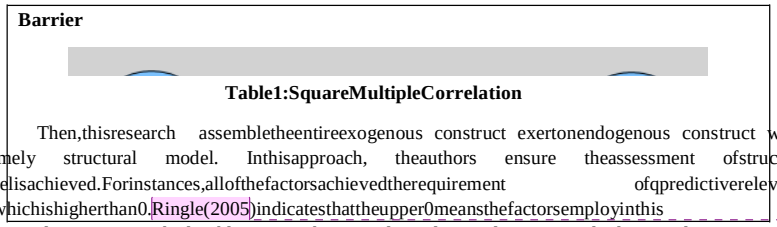


Table1:SquareMultipleCorrelation

Then,thisresearch assembletheentireexogenous construct exertonendogenous construct which isnamely structural model. Inthisapproach, theauthors ensure theassessment ofstructural modelisachieved.Forinstances,allofthefactorsachievedtherequirement ofqpredictiverelevance (Q)whichishigherthan0.Ringle(2005)indicatesthattheupper0meansthefactorsemployinthis areasarerelevanttoresearched.Table2presenttheoriginalsample,samplemean,standarderrorand T-statisticsforeachpathonceexecutedthebootstrappingtechniqueinSmartPls2.0.

Thefindingssuggestthatthreeoutoffourconstructnamely Barrier,BenefitandGovernment havesignificantimpactonMotivation.Instead,onlyonepathbetweenChallengefactorandMotivation isexpected doesnothassignificant impact. Inparticular, Benefitfactor isperceived themostoft-statisticswhichmeansthatBenefitisthemostcontributed conformityofsquaremultiplecorrelation testpreviously. Afterwards, thisresearch paper willbeextending topractice Non-parametric, Non-parametricconfidencesetintervalandPermutationapproachestoMulti-groupanalysisinPLS-SEM.

FullModel	OriginalSample (O)	Sample Mean(M)	StandardError (STERR)	TStatistics (|O/STERR|)
Barrier->Motivation	0.082066	0.083236	0.031514	2.604121***
Benefit->Motivation	0.683311	0.681209	0.037681	18.133986***
Challenge->Motivatio	0.017979	0.022381	0.031034	0.579353
Government->Motivation	0.127794	0.129892	0.035932	3.556564***

Table2:FullModel

Firstly, theauthorcarries onpermutation tomulti-group analysis followed byotherapproaches. All findingsrelatedonthisapproachesarepresentedinTable3:

Comment [A92]: Not in reference page

Comment [A93]: The title of the Table should in heading up

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

ANonParametricApproachtoMulti-groupAnalysis

Comment [A94]: Table number is missing

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

Motivation				
Non-Parametric ConfidenceSet Interval	**Male**	**Female**	**LowerandUpper (95%biascorrected)**	**Confidence Interval**
Barrier->Motivatio	0.078119	0.0776	[0.073943,0.083057]	FallsinRange (N.S)
Benefit->Motivatio	0.688298	0.6922	[0.683641,0.694358]	FallsinRange (N.S)
Challenge->Motivatio	0.012209	0.0134	[0.017037,0.025763]	NotinRange(Sig)
Government->Motivation	0.124517	0.1197	[0.118582,0.128819]	FallsinRange (N.S)

Table3:FindingsofNon-Parametric Test

Comment [A95]: Not properly done

*:P-level≤0.10;**:P-level≤0.05;***:P-level≤0.01;N.S:NotSignificant;Sig:Significant

Table3isnotonlypresentsthefindingofpermutation, non-parametric, andnon-parametric confidencesetintervalapproachesbuttheresultforeachgroupsincludingformaleandfemalearelaid out.By inspectingthroughforeachapproachincludingthefullmodel,almostapproachessuggestthe similarfindingsunlessnon-parametric confidencesetapproaches. Thefirstpart,theauthorsseparate thefullmodeltobegroup 1(Male) andgroup 2(Female) andexecute usingPLSalgorithm. PLS algorithmisdevelopedbyLindgrenet.al(2005)andthetruenameiskernelPLSalgorithm.But,now thisapproachhasbeenexpandtobeknownasWideKernelPLSalgorithmbyMeviket.al(2011).

Formalegroup,thereare two independentfactorsnamelyBenefitandGovernmenthave significantimpactonMotivationduetothevalueisabsolutegreaterthan1.96.Previously,theBarrier factor isa significant impact on Motivation before separately. Thus, itcan be proved that the significantimpactisinfluenced bycharacteristics ofeachgroup.Inotherwords,Malegroupsdonot haveanyobstacle toaffecttheMotivationfactor.However,thisparticulargroupagreestoindicatethat theBenefitandGovernment canaffecttheirMotivation topronevolunteerism program. Inaddition, theydecide theChallenge factorisdonoteffect onMotivation. Thus,therelated partiesshouldbe address that Male group donot have anyproblem tobe active involunteerism program and they certifiedthisprogramisgoodfortheircountry.

Forfemalegroups,theyhavea differentviewtoexplainthesignificantofvolunteerism.They agreethatBenefit,BarrierandGovernment canaffecttheirMotivation toparticipate involunteerism program.But,theyalsohaveasameviewwiththeMalegrouptosuggestthatChallengefactordonot affecttheMotivation.Thus,therelatedpartiesshouldprovideanaffirmativeactiontoidentifywhether thisfactormayoneofthemainproblems topreventthemactiveinvolunteerism program. Besides, Female groups indicate the Barrier factor is one of the factors hinder them toprone inparticular program.Thisis becausesomeoftheirparentsdonotgivepermissionto lettheirdaughterto involveof suggestedprogram.

Forpermutationtestwhichisoneofthefreedistributionin whichdonotreliesonstatistical assumption executed. As aforementioned, permutation test is appropriate to conduct multi-group analysistoidentifywhetherthegendergroupsisinfluenced onMotivation. Thefindingssuggestthat allofthesefactorsagreethecausaleffectbetweenexogenousandendogenousconstructsdonotaffect bygendergroups.BasedontheTable3,theauthorspresentcharacteristicsoftableforpermutationtest thatshouldbeaddressed.In thiscase,originalsample(pathanalysis)formaleandfemalearepresented followed bydifferent and probability value. Different valuesare attained based on the different betweenmeanof maleandfemalerespectively.Thelast columnpresentof probabilitylevelthatcanbe calculatedbasedonthepreviouslyformulagiven.Thismethodneedsbilateral stepstoconsiderforthe wholeperspectiveinorderto preventunfairassumption.Thedifferentbetweenmaleandfemalecanbe presentedasbelow:

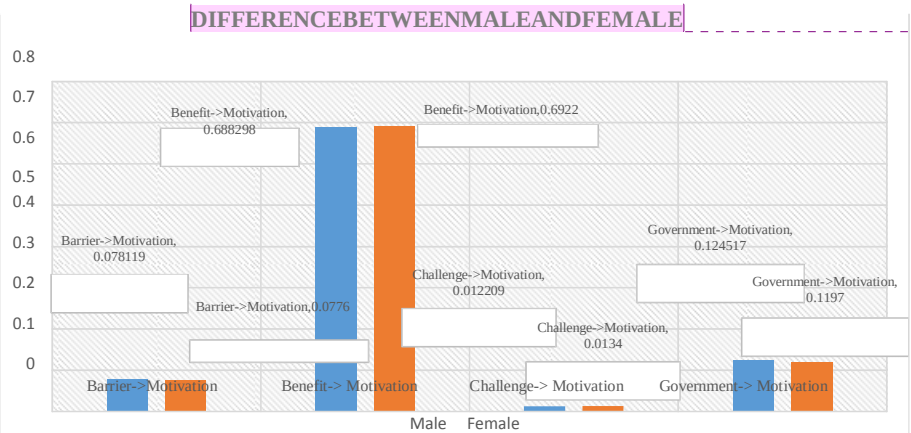


Figure2:DifferencebetweenMaleandFemale

Fornon-parametric testtomulti-group analysis,theauthorsalsopresenttheoriginalsample meanofmaleandfemalesameaspermutationtest.However,thethirdcolumniserrorprobabilitythat willbecalculatedbythePLS-Hubonasheet.Thelastcolumnisprobabilityleveliscountedbasedon theformula:1-ErrorProbability.Inordertoilluminatethestepofnon-parametrictest,theauthorshows thestepasbelow:

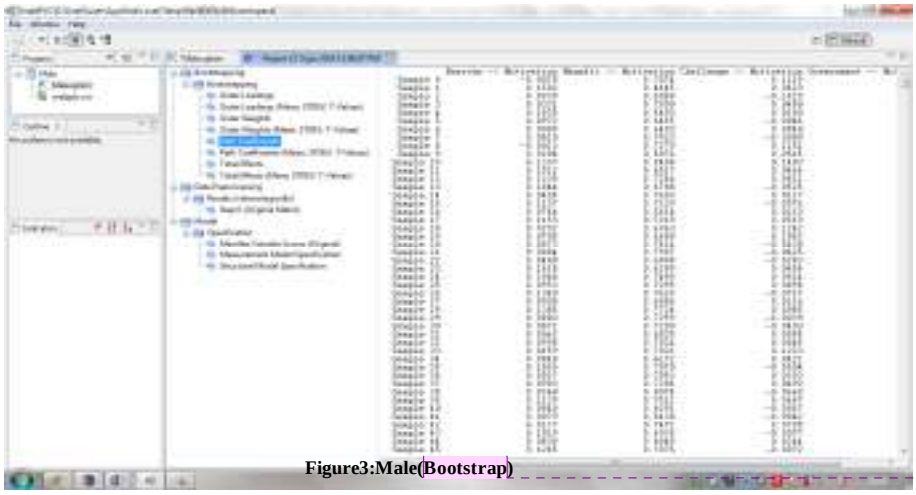


Figure3:Male(Bootstrap)

1. Split data into two groups (Male and Female) and execute respectively. In this case, the authorsstartonmalegroupsandtheresultwereappearedindefaultreport.
2. Then,executeBootstraptechniquetoobtainthestandarderrorandT-statisticsformalegroup.
3. Theresult waspresented for each path and sample. Inthe first column ispresent Barrier Motivation.Thus,thescholarsshouldcopythefirstcolumnandpasteinthecolumnof100 bootstrapvaluesofgroup1.

Comment [A96]: Be below the figure

Comment [A97]: Should

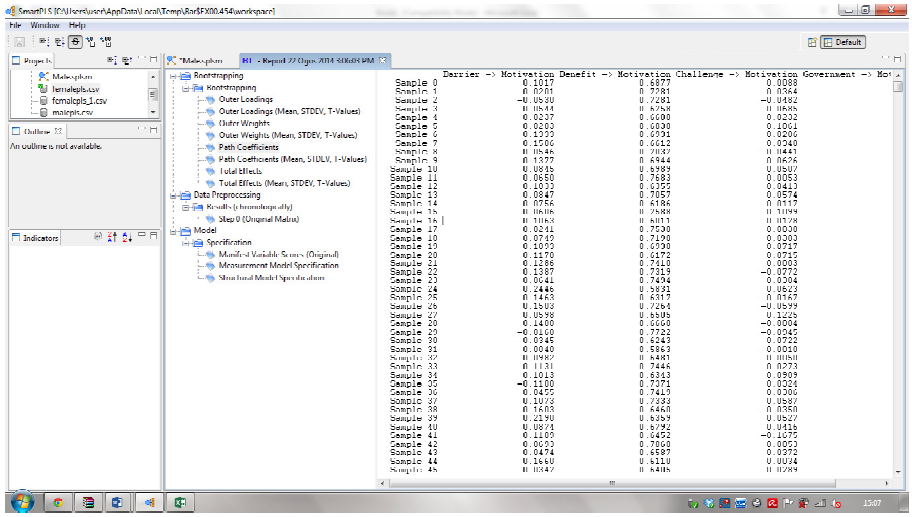


Figure4:Female(Bootstrap)

1. Theprocessforfemalegroupissimilarasmalegroup.
2. SincetheauthorscopyBarrierMotivationfromMaledata,thus,thesamefactorshouldbe addressedandpastein100bootstrapvaluesofgroup2.
3. Parameterofgroup1representfororiginalmeanofMalegroupaswellasforFemalegroup forparametergroup2.
4. Figure 5 present an example of PLS-Hubonato execute the non-parametric multi-group analysisasfollows:

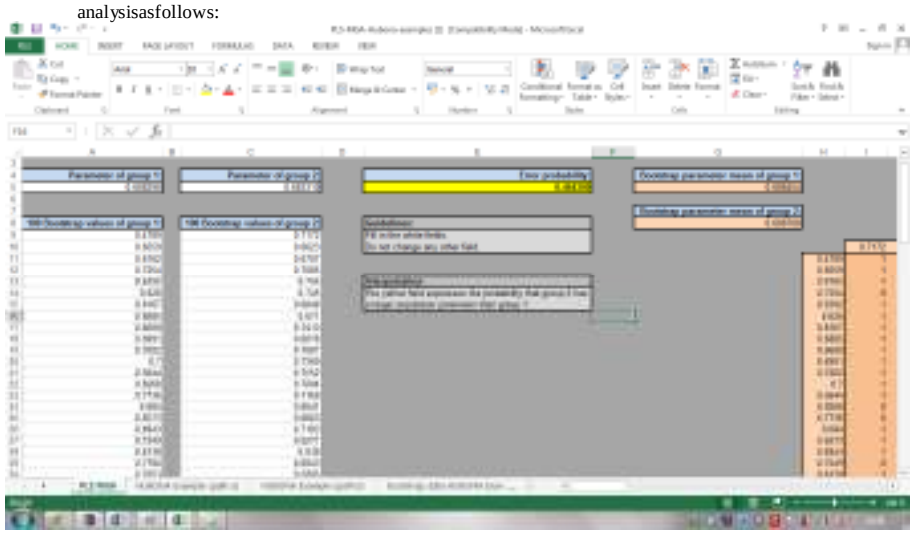


Figure5:Non-ParametricTest

ForNon-parametric confidencesetinterval test,onlyoneoutoffourindependent factor is indicatehasasignificant impactonMotivation whichisChallenge factor.Byinspecting throughfor

each approaches applied, non-parametric confidence set interval test is the only one suggests the difference result.Thus,itcanbeperceived thatthedifferentapproaches willeffectofourfindingto carryontheresearchmoreprofound.However,thisapproachisagreedtoindicatethattheotherfactor aredo notsignificantimpactinlineofpreviousapproaches.

ExampleofBarrierMotivationinGroup2(Female):

AverageMean:0.0785
StandardError:0.0398
SampleSizeforfemalegroup:293
95%confidencelevel=1.96(Referz-testtable)
ConfidenceInterval: $\frac{\text{▪}\cdot\text{▪}*+,}{\sqrt{\&+*}}$ =0.002325;
=0.002325x1.96(95%confidencelevel)
Margin =0.004547
UpperInterval:0.0785+0.004547=0.083057
LowerInterval:0.0785–0.004547=0.073943

Theprocessofotherexogenousconstructsissimilarasabove.

CONCLUSION

This research paper intends to carry on the multi-group analysis using three proposed approaches namelypermutation test,non-parametric test,andnon-parametric confidence setinterval. To date, the authors use the same data by the distinct approaches to determine whether these approaches would provide thesame ordifferent findings. Allofthese approachesare known non-parametric,meansthat,theydonotreliesanystatisticalassumptionandfreelyforresearchersto further their studies. Moreover, the authors interest to present the scholar on how to implement these approaches sothatthereaders knowverywellwhichapproach iseasytoimplement basedontheir knowledge.Basedonourexperience andobservation, non-parametric confidence setapproach isthe easiest waytoprovide theprobability levelratherthantheotherapproaches. However, iftheother researcher interesttoapplynon-parametric test,thescholars areadvisedtoattainthespreadsheet of Henseler(2009)toascertainthemcarryontheirresearch. Moreover, thepermutation testalsocanbe performedbutthescholarsshouldbecarefulsincethebilateralmechanismisapplied.

Thefirstpartis abouttheusageofSquareMultipleCorrelation(R^2)thathasbeencarryonthis research.Inbasically,R^2isusedtolettheresearcheridentifywhethertheirresearchisadequateornot fortheir research. However, the authors suggest thatthismethod isnot onlylimited tojustify the structural model but also helps the scholars to identify which one of the independent variable is importance andperformance regardless ofstatistical assumption. This approach isjustify since the most importance and performance factor namely Benefit construct isconstantly performed for the subsequentanalysis.

Afterwards, theauthorsperformed threeapproaches tocarryonthemulti-group analysison the basis of formula and step bystep provided. Based onthe findings presented, two approaches namelypermutationtestandnon-parametric testsuggestthesimilarresult,inparticular,gendergroups donotinfluences thecausal effect between fourindependent variable onMotivation (endogenous construct).Nevertheless, non-parametric confidencesetintervalrevealthattheChallengefactoristhe onlyonefactor hassignificant influenced bygender grouponMotivation, inawhile, otherfactors providethesameresult.

RECOMMENDATION

Thissubtopicisexisttoimprovethelimitationthathasbeenfacedbyauthorstoaccomplish theresearch work. Thefirstthings isabout thesample sizeusedshouldbeenlarged forthefuture researchinordertoensurethefindingsmoreaccurateandmeaningful.Thisisbecausethesamplesize canbeamainproblemthatcausestheapproachpresentdifferentresult.Thesecondthingsareabout the moderatorvariable applied. Inthis case, the author stress on gender group tobe a moderator variablebasedontheliteraturereviewhasapotentialtomoderatestheinfluencebetweenexogenous andendogenous construct. However, almost approaches suggest thatthisgender groupdonothave

Comment [A98]: removed

Comment [A99]: no need for citation

Comment [A100]: the importance of SMC has been established by researchers what is the significance of your findings related to previous reseatrch

Comment [A101]: grammar

Comment [A102]: VB-SEM could be accomplish irrespective of the sample size

potential toinfluence thecapability ofMotivation. Thus, itmight beagoodreason forauthors to proposeothercategoricalorcontinuousfactortosupportourtheoreticalinthenextresearch.

Thethirdpart,theauthorssuggestthisapproaches shouldbeemployinSmartPLS2.0since the practice of multi-group analysis has become a main research for academicians toextend their research. The fourth part, PLS-SEM is more interesting once the developers also provide the approachesformorethantwogroupsinmulti-groupanalysis.Thelastpartis aboutthe assessmentfor measurement andstructural modelshouldbeperformed. Thisisbecause someresearcher interestto justifytheirworkbasedonassessmentinordertojustifytheirworktoreaders.

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Comment [A103]: Not complete

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Page 1: [1] Comment [A14]	Abdulwahab	19-Nov-14 2:46:00 PM

Line 24-27 The keywords should be reduced to 5

Page 1: [2] Comment [A16]	Abdulwahab	19-Nov-14 2:48:00 PM

Line 32 for many research area

Page 1: [3] Comment [A17]	Abdulwahab	19-Nov-14 2:50:00 PM

Line 34 by the researcher in executing their with ease.

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Page 1: [5] Comment [A19]	Abdulwahab	19-Nov-14 2:55:00 PM

Line 37 wrong citation the year in parenthesis must be shown.

Page 1: [6] Comment [A23]	Abdulwahab	19-Nov-14 3:00:00 PM

Line 39 replace by (Lohmoller, 1989).

Page 1: [7] Comment [A24]	Abdulwahab	19-Nov-14 3:13:00 PM

Line 40 popular compared to

Page 1: [8] Comment [A28]	Abdulwahab	19-Nov-14 3:02:00 PM

Line 42, replace by Most researchers

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Line 42 , Prior researches list the researchers

Page 1: [10] Comment [A33]	Abdulwahab	19-Nov-14 3:20:00 PM

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