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Analysis of Partial Least Squares on Split Path Models: Underpinning Delone & Maclean Theory

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Abstract: The analysis of partial least squares utilizing Structural Equation Modeling is well known as a second generation technique .Its true that , this technique has not been fully utilized in the field of research to handle complex data analysis in simulation and modeling by a number of researches globally. Such has been experienced in universities within African continent and specifically Postgraduate students particular in Kenya . PLS handled by SEM is considered not friendly by a number of scholars hence it has taken a low profile trend. This research aimed at analyzing partial least squares on Multiple group model comparison. Research underpinned a Delone & Mclean theory, attention is directed towards multiple group comparison of Six constructs with 36 split path diagrams. Data was adopted from the public sector from a PhD Thesis. Findings indicated that: Multiple group modeling comparison indicated that: Technical operation skills had positive significant difference on IFMIS applicability; Group Comparison yielded a lower ratio index meaning it fitted well. Information Quality model performed equally well in terms of Model Ratio Index. In terms of Goodness of fit comparison it indicated good results above the threshold. Level of IT Infrastructure delivered results of poor goodness of fit,which was not significant and had a higher ratio Index above 5, indicating a poor model fitting. All in all Partial least squares on Multiple Group Modeling Comparison was successfully utilized in measuring and analyzing the constructs of Delone & Mclean Theory. In conclusion all the five models were optimum and indicated an effective measure on IFMIS applicability, apart from Level of IT Infrastructure. Study contribution include:Techniques on Partial least squares by Structural Equation Modeling using by Splitting models Comparison, analysis by AMOS, Ratio indices. Study recommends further investigation of New Techniques for Analysis: Bootstrapping and Nested comparison.

Keywords Partial least squares (PLS), Structure Equation Modeling (SEM), Multiple Group Modeling Comparison (MGMC)

1. Introduction/Background

The Purpose of Partial least squares (PLS) path modeling has become a pivotal empirical research method in international Computing and System. Owing to group comparisons models its' important role in research on international Computing and System. This study provided researchers with recommendations on how to conduct multigroup analyses in PLS path modeling. The study performed multigroup analysis on IFMIS applicability with a number of methods in PLS path modeling, which involves multiple comparison of split path models. It has also examined *model evaluation Criteria by comparing models Goodness of fit ,chi-square differences has been examined; its results compared and lastly* assessment of the Ratio of *models by comparison ratio Indices of* across six models with plit 36 path diagrams.

Partial least squares (PLS) is a form of structural equation modeling (SEM), which can provide much value for causal inquiry in Computing, networking, communication-related and engineering research fields. Despite the wide availability of technical information on PLS, many behavioral and communication researchers often do not use PLS in situations in which it could provide unique theoretical insights. Moreover, complex models comprising formative (causal) and reflective (consequent) constructs are now common in behavioral research, but they often miss specified in statistical models, resulting in erroneous tests.

This paper attests that First-generation (1G) techniques, such as correlations, regressions, or difference of means tests (such as ANOVA or -tests), offer limited modeling capabilities, particularly in terms of causal modeling / Gaphical modeling. In contrast, second-generation techniques (such as covariance-based SEM or PLS) offer extensive, scalable, Model Nested comparison and flexible causal-modeling capabilities. Second-generation (2G) techniques do not invalidate the need for 1G technique. This paper employed second generation techniques to perform Multiple Group Models Comparisons to check and make sure that the estimates of six models are significant towards examining IFMIS Applicability.

This study utilized Analysis of Moments Structures developed by James Arbuckle [1] of Temple University. Moments refers to means, variances and covariances. Its an easy-to-use of Structural Equation Modeling (SEM). It involves knowledge of the theory of the variables under investigation and the translation of that theory into a set of linear regression equations that are simply represented by arrows connecting the variables [2]. This research asserts that *AMOS* accepts a path diagram as the model specification and provides drag-and-drop drawing tools that allow rapid model specification in intuitive and user-friendly ways. It creates more realistic models than standard multivariate statistics or multiple regression models alone. The author content that the key point of 2G techniques is that they are superior for the complex causal modeling that dominates recent research. According to Alexander [3], multiple group models involve splitting a sample or Model into groups based on a categorical variable and simultaneously estimating models for each group.

2. Literature

Despite claims that this study sampling requirements exist for PLS, inadequate sample sizes result in the same problems for either technique. Confirmatory work, PLS is an optimum technique. The author, placed high premium on ratio Indices noting that statistic (x^2) is also known as the likelihood ratio chi-square or generalized like lihood ratio. The estimation process in SEM focused on yielding parameter values so that the discrepancy between this study on sample covariance matrix (S) and the SEM estimated covariance matrix is minimal. If $x^2 = 0$, the model perfectly fits the data (*i.e.*, the predicted correlations and covariance's equal their observed counter parts).

The author spitted a number of models: Technical Operation Skills (TOS) model, Magement Skills (MgtS) model, Level of IT Infrastructure (LOIT) model, Service Quality (SerQ) model, System Quality (SysQ) model and Information Quality (InQ) model. Model parameters were equated across groups multiple group models to be used to test if any model parameter or Split Path Diagram differs across groups by comparing models in terms of: Goodness of Fit, Ratio Indices, Factor Loading, Squared Multiple Coefficients, Variance Error, Means; all traditionally used in SEM contexts [4].

This study contends that its essential to consider the value of chi square increases, the fit of an over identified model becomes increasingly worse. This Research assures that Chi Goodness of fit was not used as a sole indictor of model fit [5]. For that reason several other Goodness of fit (GOF) measures has been employed to overcome problems with chi-square as examined below in analysis Chi square ratio indices. To address the problem of chi square increases, the study performed ($\mathbf{X}^2$/df) ratio index, also known as the normed chi square in attempt to make it less dependent on sample size. The *GFI* and *AGFI* can be classified as absolute indices. The parsimony goodness-of-fit index [6] corrects the value of the GFI by a factor that reflects model complexity, but it is sensitive to model size.

This research considered a good number of goodness of fit test measures*: Normed Fit Index (NFI), Relative Fit Index (RFI) & Comparative Fit Index (CFI):* The NFI is one of the original incremental fit indices introduced by Bentler and Bonnet [7]. It is a ratio of the difference in the value for the fitted model and the null model divided by the value for the null model. It ranges between zero to one; at level NFI > 0.9; a Normed fit index of one indicates perfect fit. The relative Fit Index [8] represents a derivative of the NFI; as with both the NFI and CFI, the RFI coefficient values range from zero to one with values close to one indicating superior fit [9].

According to Bentler [10], the CFI is an incremental fit index that is an improved version of the NFI. The CFI is Normed so that values range bet this study zero to one, with higher values indicating better fit [7, 9]. This study

therefore argues that, the CFI has many desirable properties, including its relative, but not complete, insensitivity to model complexity; study chose it because it's among the widely used indices. CFI values above 0.90 are usually associated with a model that fits well. But a revised cut off value close to 0.95 was suggested by Hu and Bentler [9].
This research attest that its essential to utilize Tucker Lewis Index [11] which was conceptually similar to the NFI, but varies in that , it is actually a comparison of the Normed chi-square values for the null and specified model, which to some degree takes into account model complexity. Models with good fit have values that approach one [9], and a model with a higher value suggests a better fit than a model with a lower value. The research attest that Root Mean Square Error Approximation is one of the most widely used measures it was first proposed by Steiger and Lind [12]. It attempts to correct for the tendency of the GOF test statistic to reject models with a large sample or a large number of observed variables.
This research argues that RMSEA less than 0.5 values indicate better fit. The Root Mean Square Residual represents the average residual value derived from the filling of the variance- covariance matrix for the hypothesized model to the variance covariance matrix of the sample data (S). The research argues that RMR values represent better fit and higher values represent worse fit. Recommendation by Rule of thumb, value of RMR is < 0.02. The closer RMR is to 0, the better the model fit. Rule of thumb: RMR should be < 0.10, or 0.08, or 0.06, or 0.05 or even 0.04 [15].

2.2. Model Evaluation Criteria

This research employed Partial least squares by Structural Equation Modeling which is a second generation techniques to perform Multiple Group Models Comparisons to check and make sure that the estimates of six models with a total of 36 path diagram. It is one of the most widely used SEM techniques in the evaluation especially in the social and behavioral sciences [13]. Squared multiple correlations are independent of units of measurement. Amos displays a squared multiple correlation for each endogenous variable [15]. This research highlighted foundation planting on 36 split path model diagram, attesting that Path analysis is a technique used to examine causal relationships between two or more variables.
It involves a set of simultaneous regression equations that theoretically establish the relationship among observed variables in the path model for analyzing six models with a total of 36 path diagram, which was well utilized to examine IFMIS applicability. The author contend that path analysis extends the idea of regression modeling and gives the flexibility of quantifying indirect and total causal effects in addition to the direct effect which is also possible in regression analysis for constructs in IFMIS applicability [15]. This study argues that it gives more flexibility and prediction of variables which allows the influence of IFMIS applicability of variables directly as well as indirectly through intention as a mediating variable. The author further postulates that it shares principles of regression analysis: Path analysis model focuses on relationships of multiple observed variables analysis of several regression equations simultaneously such as 36 path diagram.
In this study, the primary interest in Partial least squares Structural Equation Modeling is the extent to which a hypothesized data "fits" the models, adequately describes the sample, ideally evaluates spited models and in turn utilized to examine IFMIS applicability. This research considered chi-square goodness of fit (GOF).The author assures that chi-square goodness of fit was not used as a sole indictor of model fit [5], in this case several other Goodness of fit (GOF) measures has been employed to overcome problems with chi-square.

2.3. Chi-Square Difference Test

The chi-square statistic is an overall measure of how many of the implied moments and sample moments differ. CMIN (Chi-square statistic ($\chi 2$) is the minimum value of the discrepancy. In the case of maximum likelihood estimation, CMIN contains the chi-square statistic. The more the implied and sample moments differ, the bigger the chi-square statistic, and the stronger the evidence against the null hypothesis. P value is the probability of getting as large a discrepancy as occurred with the present sample under appropriate distributional assumptions and assuming a correctly specified model. The fit statistics addresses the problems with chi-square, which operate the ($\mathbf{X}^2$/df) ratio, also known as the normed chi square in an attempt to make it less dependent on sample size [16]. So P is a "*p value"* for testing the hypothesis that the model fits perfectly in the population adopted from the public sector ,used to determine IFMIS applicability. Therefore, this is a method to select the model by testing the hypothesis to eliminate any models that are inconsistent with the available data. Although Arbuckle [1] claimed that it is not clear how far from 1 we should let the ratio get before concluding that a model is unsatisfactory.

In contrast, Byrne [17] suggested that ratio should not exceed 3 before it cannot be accepted. Since the chi-square statistic ($\chi 2$) is sensitive to sample size it is necessary to look at others that also support goodness of fit. Measures Based on the Population Discrepancy; The most commonly used is RMSEA which is the population root mean square error of approximation. Comparisons to Baseline Model with three significant indices are NFI, TLI, and CFI. NFI is the normed fit index, while TLI is the Tucker-Lewis coefficient and CFI is the comparative fit index. CFI is truncated to fall in the range from 0 to 1, values bigger than 1 are reported as 1, while values less than 0 are reported as 0.

Research show that the relative chi-square should be in 5 or less reflects good fit or acceptable fit [16]. The other goodness of fit indices can be categorized into three sets: absolute; incremental; and parsimony fit measures (Hair et al., 2006).Root mean square residual (RMR), measures the average of the residuals between individual observed and estimated covariance and variance terms .This study RMR and standardized root mean square residual (SRMR) values represent better fit and higher values represent worse fit [5].

3. Methodology

3.1. Design, Population and Data collection Tools: This research employed a cross-sectional descriptive survey. Surveys are a popular method of collecting data. The research used was Stratified Simple Random design in achieving the Homogenous population of respondents from the Heterogonous. Secondary data was adopted from Thesis Research by Sanja, M., M., (2017) for PhD thesis whose data was collected from Public Sector by use of questionnaires. The sample size was 300.

3.2. Analysis: This research employed AMOS graphics to compare multiple samples across the same measurement instrument by means of Partial least squares: TOS Model_1, MgtSModel_2, LOIT Model_3, SystQModel_4, ServQModel_5, InfQ and Model_6. The research tested the Ratio Indices, Chi-square difference in respect to the Degree of freedom, tested the Goodness of model Fit, factor loadings for Six different Models.

4. Findings

4.1. Multiple Group Models Comparisons of TOS Model_1 by Ratio Indices

Analysis done on unobserved variables; Technical operation Skills and use of IFMIS System included spitted models of: Technical operation Skills-1,Technical operation Skills-2, Technical operation Skills-3,Technical operation Skills-4,Technical operation Skills-5,Technical operation Skills-6,Technical operation Skills-7and Technical operation Skills-8.After a random split into eight (Octal) sub model each path model was scored separately. The portion of the model that specifies how the observed variables depend on the unobserved, or latent, variables is called the measurement model. The current model has eight distinct measurement sub models (Figure 4.1).

The scores of the 8 split-model subtests, TOS-1, TOS-2, TOS-3, TOS-4, TOS-5, TOS-6, TOS-7 and TOS-8 are hypothesized to depend on the single underlying latent variable known as Technical operation Skills which is operationalised to depend on IFMIS applicability . According to the model (Figure 4.1), scores on the 8 subtests may still disagree, owing to the influence of measurement errors. Study employed, X^2, df, P, X^2/df, TLI, AGFI CFI, NFI, RMR, RMSEA and GFI because they are independent of model complexity and sample size. Results obtained indicate that: TOS Octal Split Model_1 yielded Ratio Index: $\chi 2$ (df = 82, N = 300) = 26.913, p = 0.013 hence <0.05 which indicates that its significant. Ratio index X^2 / df = (3.2672) was less than 5 in other words the model is a good fit .The author considered fit statistics to address the problems with chi-square, with ($\mathbf{X}^2$/df) ratio, chi square attempts to make it less dependent on sample size .The relative chi-square should be 5 or less to reflect good fit or acceptable fit [16].

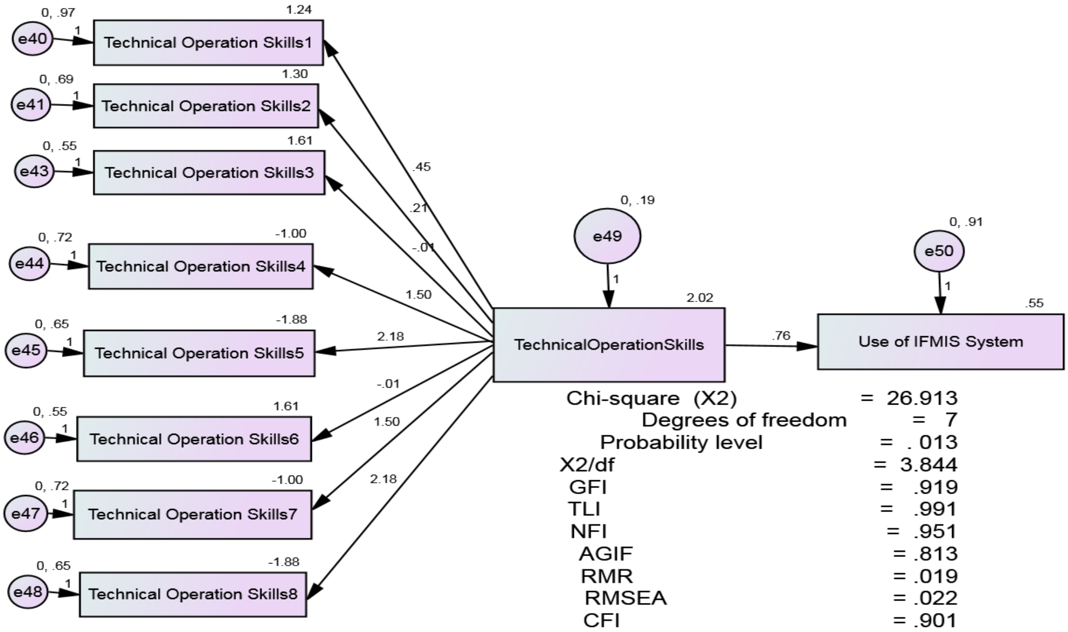

Figure 4.1: TOS Octal Split Model_1(Source : 2017 PhD Thesis Sanja M.M)

4.2. Multiple Group Model Comparisons of MgtS Model_2 by Ratio Indices

Analysis of multiple group model Comparisons was employed on unobserved variables, Management Skill Model_2 and IFMIS applicability tests: MgtS Model-1, MgtS Model-2, MgtS Model-3, MgtS Model-4, MgtS Model-5, MgtS Model-6, MgtS Model-7 and MgtS Model-8. After a random split into eight sub model each path model was scored separately. The scores of the 8 split-model subtests are hypothesized to depend on the single underlying latent variable Management Skill which is also operationalised to depend on IFMIS applicability. Scores as indicated in figure 4.2. Results obtained indicate that: Management Skill Split Model yielded Ratio Index: X2 (df = 9,N = 300) = 20.013, p = 0.000 hence a departure from $p < 0.05$ indicated a significant difference in other words Management Skills Split Model is a strong significant of IFMIS applicability ; Results indicate that Ratio index X^2 / df = (2.224) is less than 5 in other words the model is a good fit [16].

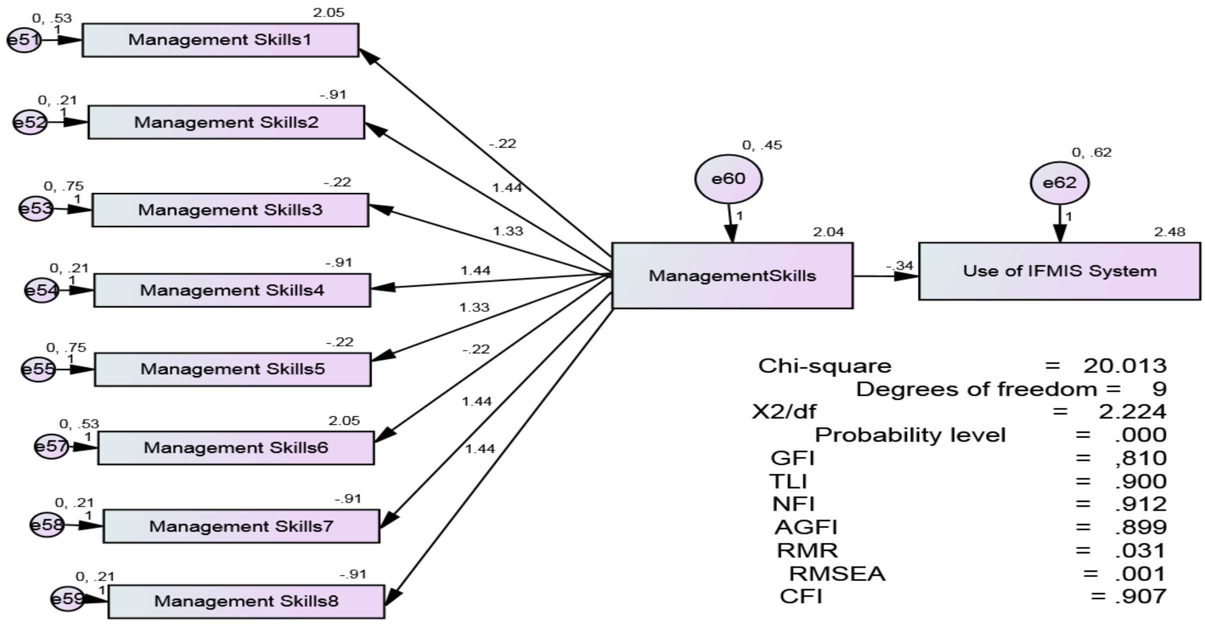

Figure 4.2: MgtS Octal Split Model_2 (Source: 2017 - PhD Thesis Sanja M.M)

4.3. Multiple Group Models Comparisons of LOIT Model_3by Ratio Indices

Figure 4.3 shows that results on unobserved variables are: LOIT Model_3 and IFMIS applicability tests: LOIT Model-1, LOIT Model-2, LOIT Model-3, LOIT Model-4, LOIT Model-5, LOIT Model-6, LOIT Model-7 and LOIT Model-8. After a random split into eight sub model each path model was scored separately. The current model has eight distinct measurement sub models. The scores of the 8 split-model subtests depend on the single underlying latent variable Level of IT Infrastructure which is operationalised to depend on IFMIS applicability .According to the model (Figure 4.3), scores on the 8 subtests may vary. Results obtained indicate that: Level of IT Infrastructure Split Model yielded Ratio Index: X2 (df = 72, N= 300) = 369.612, p=0.643 hence a departure from $p < 0.05$ indicated a no significant difference; Results indicate that Ratio index , X^2/df= (5.1335) is greater than 5 in other words the model is not a good fit.

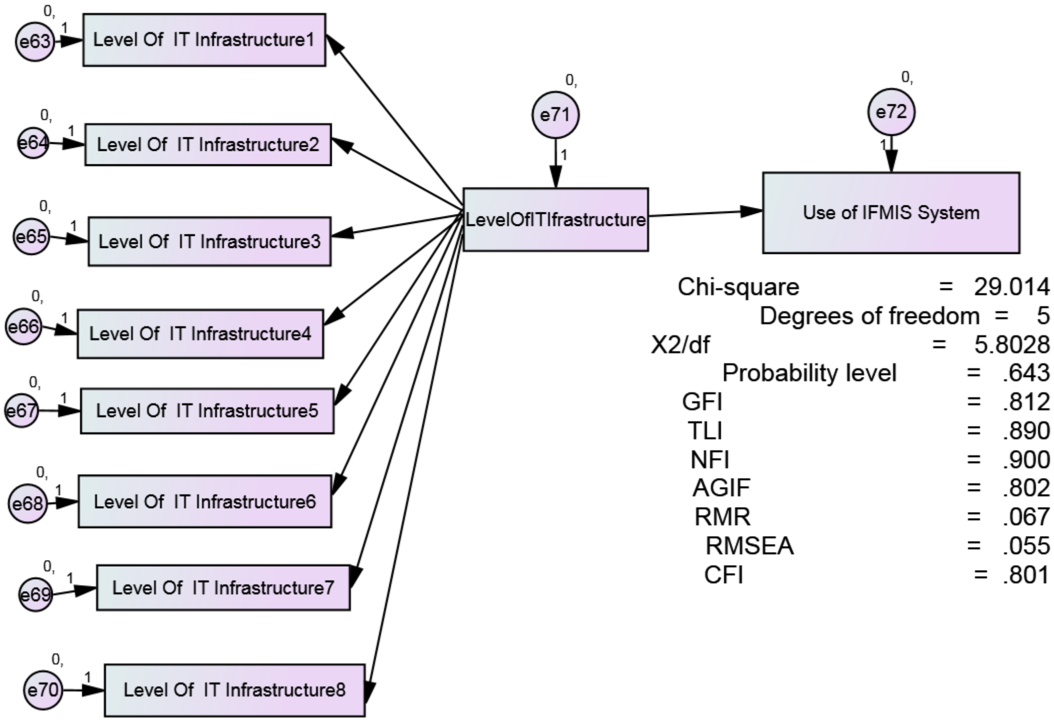

Figure 4.3: LOIT Octal Split Model_3 (Source: 2017 PhD Thesis Sanja M.M)

4.4. Multiple Group Model Comparisons of Information Quality Model_4 by Ratio Indices

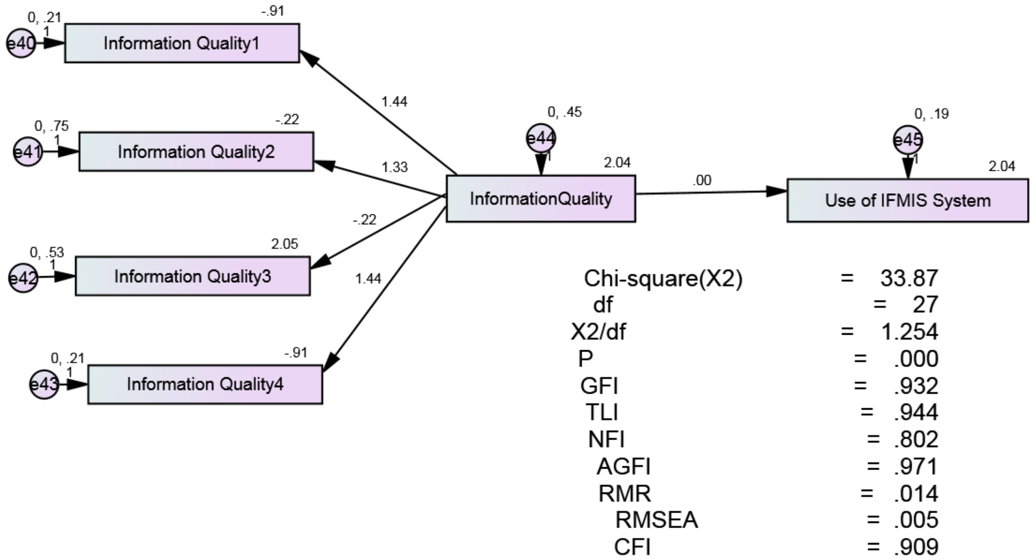

Figure 4.4: Information Quality Split Model_4 (Source : 2017 PhD Thesis Sanja M.M)

Tests on unobserved variables indicate that Information Quality and IFMIS applicability tests yielded results for the following split models: Information Quality-1, Information Quality-2, Information Quality-3 and Information Quality-4. The scores of the 4 split-model subtests include: InfQ-1, InfQ-2, InfQ-3, InfQ-4 hypothesized to depend on the single underlying latent variable known as Information Quality, which also hypothesized to depend on IFMIS applicability.

Model fit: The research tested the Model fit under the following methods: X^2, df, P, X^2/df, TLI, AGFI CFI, NFI, RMR, RMSEA and GFI (Figure 4.4)

4.5. Multiple Group Model Comparisons of Service Quality Model_5 by Ratio Indices

Service Quality Model for Unobserved variables, System Quality and Use of IFMIS System tests: System Quality-1, System Quality-2, System Quality-3 and System Quality-4 .Sub model each path model scored separately .The scores of the 4 split-model subtests, SystQ-1, SystQ-2, SystQ-3 and SystQ-4 are hypothesized to depend on the single underlying latent variable System Quality is operationalised to depend on Use of IFMIS System. The 4 subtests may still disagree, owing to the influence of measurement errors. Model fit: The research tested a number of methods as indicated in figure 4.5.

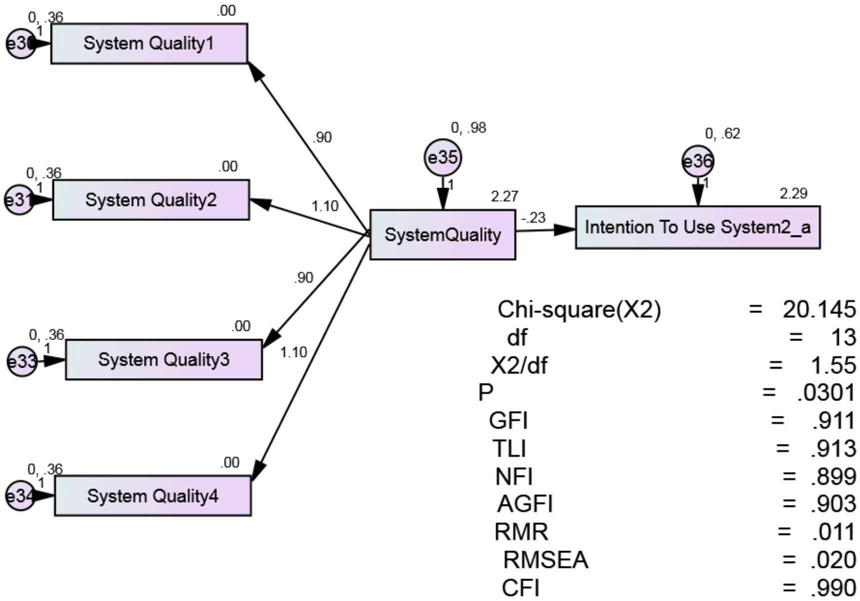

Figure 4.5: System Quality Split Model_5 (Source: 2017 PhD Thesis Sanja M. M)

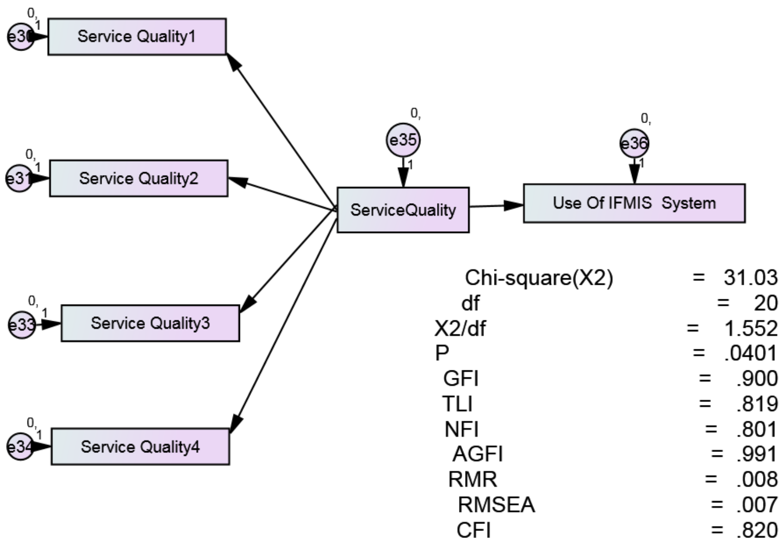

Figure 4.6: Service Quality Split Model_5 (Source: 2017 PhD Thesis Sanja M.M)

4.6. Multiple Group Model Comparisons of Service Quality Model_6 by Ratio Indices

The current model has four distinct measurement sub models. The scores of the 4 split-model subtests, SystQ-1, SystQ-2, SystQ-3 & SystQ-4 are hypothesized to depend on the single underlying latent variable Service Quality is operationalised to depend on IFMIS System applicability. Results in (Figure 4.6) shows that analysis of Service Quality Model yielded the following goodness-of-fit: Χ2 (df = 72, N = 300) = 231.87, p = 0.301; RMSEA =.066 (90% CI=.000 -.122) ; Ratio = 3.01078 ; PCFI = .444; AIC = 52.943. In general Model_5 had chi-square (231.87), df (72) while P-level (0.301) whose ratio x2 / df = (3.01078).

4.7. Multiple Group Model Comparison with Chi Square Differences

The test statistic value for the Chi-square difference test is merely the difference between the Chi-square test statistic values of the multiple group measurement models .The associated, degrees of freedom are merely the difference between the degrees of freedom of the multiple group measurement models under the null and the alternative hypotheses.

4.7.1. TOS Model_1 and MgtS Model

Multiple group Model Comparison with Chi-Square differences was performed between two models: Technical Operation Skills Split Model_1 and Management Skills Split Model_2**:** Results :(Model_1 -Model_2) = (26.913- 20.013) = 6.90 . Hence difference between Model_1 and Model_2 = 6.90

4.7.2. Delone & Mclean Theory

Results indicate that model_3,yielded in terms of goodness of fit, on average 0.800 below the threshold 0.9, the model assessed indicated that it was not significant p = 0.643, its ratio index was above 5 ,i.e (5.8028),While model_4, was the best with ratio index far from five (1.254). Where Chi Square Model_4 = 33.70, Model_5 = 31.030. Results on Chi Square Differences indicate that: Model_4 - Model_5 = (33.70 - 31.030) = 2.84. Hence difference between Model_4 and Model_5 = 2.84Model_4 = 33.70, Model_5 = 31.030 and Model_6 =20.145. Results posted show that Chi Square Differences indicate that: Model_4 - Model_6 = (33.70- 20.145) = 13.725, while Differences Model_5 - Model_6 = (31.030 -20.145) = 10.885.

4.8. Finding of Goodness of Fit

The research employed Test of Goodness of Fit with operation on various methods: Chi Square (X^2), df, P, X^2/df, TLI, AGFI, CFI, NFI, RMR, RMSEA and GFI, Results in (Table4.8) indicated that; Model_1 had RMR = 0.019 indicating good fit, RMSEA = 0.022 which is good fit, TLI= 0.991 best fit, NFI=0.951 good fit, with p= 0.013 less that p =0.05 hence significant. Model_4 yielded RMR= 0.014 indicating good fit, which is good fit, TLI=0.944 best fit, NFI=0.951 good fit, GFI= 0.932, AGFI = 0.971 Showing good fit (AGFI; Joreskog & Sorbom,1981) with p= 0.013 less than p = 0.05 hence significant .Results on Root-mean-square error of approximation (RMSEA) = 0.005: it is equal to 0.00 (<0.05 is acceptable), RMSEA= 0.005 Goodness-of-fit index (GFI): 0.966 (>0.90 is acceptable. Similar study by Hui [14], confirm that, NFI values above 0.90 are good. RFI, IFI, TLI, and CFI values close to 1 indicate a very good fit.

Table 4.8: Summary of Overall Models Goodness of Fit

Scale	Model_1 TOS	Model_2 MgtS	Model_3 LOIT	Model_4 InfQ	Model_5 SystQ	Model_6 ServQ
Chi-Sq(X^2)	26.913	20.013	29.014	33.87	20.145	31.03
Df	7	9	5	27	13	20
P	0.013	0.000	0.643	0.000	0.0301	0.0401
X^2/df	3.844	2.224	5.8028	1.254	1.550	1.552
GFI	**0.919**	0.810	**0.812**	0.932	0.911	0.900
TLI	**0.991**	0.900	**0.890**	0.944	0.913	0.819
NFI	**0.951**	0.912	**0.900**	0.802	0.899	0.801
AGFI	0.813	0.899	**0.802**	0.971	0.903	0.991
RMR	**0.019**	0.031	**0.067**	0.014	0.011	0.008
RMSEA	**0.022**	0.001	**0.055**	0.005	0.020	0.007
CFI	**0.901**	0.907	**0.801**	0.909	0.990	0.820

Model_3 yielded RMR= 0.067 indicating poor fit, TLI= 0.890 below 0.9 hence poor fit, GFI= 0.812 > 0.9 poor fit, AGFI = 0.802 poor fit .than p =0.643 had no significant difference. Results on Root-mean-square error of approximation = 0.055 was closer to cut point (<0.05 is acceptable) Goodness-of-fit index (GFI): 0.966 (>0.90 is acceptable. Similar study by Hui [14], confirm that, NFI values above 0.90 are good. RFI, IFI, TLI, and CFI values close to 1 indicate a very good fit.

5. Discussions

5.1 Multiple Group Model Comparisons of Chi Square Difference

The goal of testing for measurement invariance is to determine if the same SEM model is applicable across groups. A Multiple Group Model Comparisons difference bet this study Chi-squares performed among 3 models: Technical Operation Skills Split Model_1and Management Skills Split Model_2**:** Results indicated that: (Model_1- Model_2) was 6.90. Multiple Group model Comparison among 3 models: TOS Octal Split Model_1; MgtS Octal Split Model_2; and LOIT Octal Split Model_3 results indicate; *(Model_1)-(Model_2)*= 6.90; (Model_3 - Model_2)= (29.014 - 20.013) = 9.001,(Model_3 - Model_1) = 2.101 Difference as had a range of : 2.101, 6.90, 9.0

Based on results, model comparisons of the three models indicate Model_1 and Model_2 are significantly different and Model_3 is not significantly different from Model_1 and Model_2. The smaller Ratio indices of Model_1 indicate that Model _1 is better than Model_2 and Model_3, Similar study by Anand [19], content that Chi Square differences show a slightly big range noting that Mode_1 had a good fit and was significant, same applied to Model_2, while model_3 had a bad fit.

5.2. Delone Mclean Theory Model Chi Square Difference

The study adopted Model _4, Model _5 and Model _6 from the Theory of Delone & Mclean ,multiple Group model comparisons of Chi Square difference indicated that: Model_4-Model_5; 2.84, Model_5 and Model_6; 10.885 and Model_4 - Model_6; 13.725. Chi Square differences indicate that Model_4-Model_5 had a very small different range in terms of Chi Square difference, 2.84, while Model_4 - Model_6 had the wider range of (13.725).

Result indicates that Model_4 was significant, had the best fit overall, generally all the 3 models yielded good fit. Model comparisons of the models indicate Model_4 was the best fit, had a strong significant also in terms ratio index yielded a value far from minimum 5, hence the best model .Comparatively Model_5 and Model _6 as adopted from the theory of Delone & Mclean had significant different on IFMIS Applicability. All in all Model_4 had a strong significant different on IFMIS applicability from Model _5 and Model _6. Also the smaller Ratio indexes yielded by Model_4 indicate that Model_4 is the better fit than Model _5 and Model _6.

Multiple Group Model Comparisons of Chi Square Difference of six models show thatModel_1 and Model_4 are the best models in terms of significant, all gave smaller Ratio indice had the best goodness of fit. All values this study re above .90 indicating good fit; NFI, RFI, IFI, TLI, and CFI values close to 1 indicate a very good fit [14]. According to the Rule of thumb: a value of the *RMSEA* of about 0.05 or less would indicate a close fit of the model in relation to the degrees of freedom, Model_1 and Model_4 both achieved 0.022 and 0.005 respectively which confirm that the models is a good fit .Model_1 and Model_4 posted RMR; 0.019 and 0.014 respectively, which are in agreement with the condition set by Rule of thumb, which states that the closer RMR is to 0, the better the model fit. Rule of thumb: RMR should be < .10, or .08, or .06, or .05 or even .04 but the said models both achieved the slandered threshold and the models fitting.

According to Desurvire [20] to be paramount, based on different modal split models comparison which are based on real parameters .The results obtained are presented indicate a difference in Chi Square by modal split compared. Results indicated that; Model_1 had RMR= 0.019 indicating good fit, RMSEA= 0.022 which is good fit, TLI= 0.991 best fit, NFI=0.951 good fit, with p= 0.013 less that p =0.05 hence significant .Model_4 yielded RMR= 0.014 indicating good fit, TLI= 0.944 best fit, NFI=0.951 good fit, GFI= 0.932, similar studies show that the GFI was the very first standardized fit index [18]. In there study, they content that it's analogous to a squared multiple correlation (R^2) except that the GFI is a kind of matrix proportion of explained variance.

Thus, in this study GFI > 0.90 indicated a good fit, and values close to zero indicate very poor fit, since Model_4 yielded GFI= 0.932 its said to be very good fit. Results for AGFI = 0.971 Showing good fit [18] with p = 0.013 less than p =0.05 hence significant. Results on Root-mean-square error of approximation (RMSEA) = 0.005: it is equal to 0.00 (<0.05 is acceptable), RMSEA= 0.005 Goodness-of-fit index (GFI): 0.966 (>0.90 is acceptable. Similar study by Hui [14], confirm that, NFI values above 0.90 are good. RFI, IFI, TLI, and CFI values close to 1 indicate a very good fit.

Model_3 yielded RMR= 0.067 indicating poor fit, TLI= 0.890 below 0.9 hence poor fit, GFI= 0.812 > 0.9 poor fit, AGFI = 0.802 poor fit. Model_3 results yielded p =0.643 had no significant difference. Results on Root-mean-square error of approximation = 0.055 was closer to cut point (<0.05 is acceptable) Goodness-of-fit index GFI= 0.812 > 0.9 poor fit hence not acceptable. Study by Hui [14], confirm that, NFI values below 0.90 are bad fit. Generally RFI, IFI, TLI, and CFI values this study re all below 0.9 hence indicate a poor fit. *Normed Fit Index (NFI)* is one of the original incremental fit indices introduced by Bentler and Bonnet [7], at level NFI > 0.9 a Normed fit index of one indicates perfect fit. The Relative Fit Index [8] represents a derivative of the NFI; as with both the NFI and CFI, the RFI coefficient values range from zero to one with values close to one indicating superior fit [9].

Comparative Fit Index (CFI), according to Bentler [10], the CFI is an incremental fit index that is an improved version of the NFI. The CFI is Normed so that values range, with higher values indicating better fit [7, 9]. The Tucker Lewis Index [11] is conceptually similar to the NFI, but varies in that it is actually a comparison of the Normed chi-square values for the null and specified model. The author asserts the importance of the *GFI that it* can fall outside the range 0–1.0. Values greater than 1.0 can be found with just identified models or with over identified models with almost perfect fit; negative values are most likely to happen when the sample size is small or when model fit is extremely poor. Another index originally associated with AMOS is the adjusted goodness-of-fit index [18]. It corrects downward the value of the *GFI* based on model complexity; that is, there is a greater reduction for more complex models

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