CHAPTER 5

RESULTS

Introduction

Chapter Five covers the analyses of the data and present the statistical computations of related variables. This chapter uses descriptive statistics to summarise the demographic characteristics of the respondents. Among the statistical computations conducted include the Cronbach's alpha reliability coefficients, Pearson's correlation to assess the inter-correlations between the constructs, factor analysis, confirmatory factor analysis (CFA), measurement model validity and model fit. The AMOS program of the Structural Equation Modelling (SEM) methods was used to assess the structural model, the research mediation model and test the hypotheses. The goodness-of-fit of the structural model was evaluated using absolute and relative indices.

5.1 Sampling results

5.1.1 The data

Empirical data were obtained through a primary survey of employees working in the G-40 Government-linked companies (GLC) that are located in the capital city of Kuala Lumpur and the state of Selangor. G-40 refers to the initial group of 40 GLC in Malaysia. In tandem with the GLC Transformation Programme (2004-2015), most of these companies have in place an identified group of talents that are groomed for brighter future in their organizations. Of the 400 questionnaires distributed, a total of

342 employees volunteered to participate in the survey yielding a response rate of 85.5 percent. Measures were taken to conceal the identity of the respondents and the data collected were kept confidential. In ensuring the research ethics of the study, only aggregated results not relating to any particular participant would be analysed and reported. This sample size of 342 is larger than the minimum number of cases that are required based on the central limit theorem (CLT). According to this theorem, the acceptable sample size is 30 for each variable. With six variables in the research framework, the minimum number of cases required for this research is 180, i.e. 30 multiplied by six. By achieving 342 responses, the researcher has addressed the point of McQuitty (2004) on the importance of determining the minimum sample size required to achieve a desired level of statistical power with a given model prior to data collection. As a rule of thumb, Garver and Mentzer (1999) have proposed a critical sample size of 200 to provide sufficient statistical power for data analysis.

5.1.2 Profiles of the participating organizations

Among the GLC that responded to this study were Telekom Malaysia Bhd (TMB) , Maybank (MBB) , Bumiputra Commerce Holdings Bhd (BCHB), Malaysian Airline System Bhd (MAS), Proton Holdings Bhd, Axiata Group Bhd, Tenaga Nasional Bhd (TNB), UMW Holdings Bhd, Petronas Dagangan Bhd, Pharmaniaga Bhd, and POS Malaysia Bhd. Majority of these GLC are exemplary organizations as they are award winners. TMB was the 2006 “Data Communication Service Provider of the Year” by Frost & Sullivan Malaysia. TMB was also recognised as the winner in the Best Workplace Practices category of the Prime Minister’s CSR Awards 2009. MBB won numerous awards in 2008 and 2010 such as “Best Cash Management Bank” and “Best Trade Finance Bank” by Finance Asia Country Awards for Achievement. BCHB was awarded with “Best Investment Bank (Malaysia)” by Euromoney. MAS was the first airline to win the “World’s Best Cabin Crew” by Skytrax of United Kingdom consecutively from 2001 to 2004, and again in 2007. MAS was also one of the six airlines worldwide to be accredited with the “5-Star Airline” recognition by Skytrax for the three consecutive years of 2005-2008. Frost & Sullivan has also awarded MAS with the “Excellence in Leadership” award. Proton was awarded a Gold Award by Reader’s Digest Trust Brand 2008 for the car category for four years running since 2005. POS also won similar award in the Courier / Air Freight category for 2008. TNB was the 2008 Best Investor Relations in the Singapore market for a Malaysia company. TNB was also ranked 100 from 250 power companies worldwide by Platts Top 250 Company 2008. Axiata, formerly known as TMI International Bhd., has won numerous awards through its national and international subsidiaries in 2008. One such award was Dialog Telekom (Sri Lanka) that was ranked no.1 in Business Today’s Top 10 and Sri Lanka’s Most Valuable Brand by Brand Finance. UMW Toyota was ranked no.1 in Customer Satisfaction survey by J.D. power for three consecutive years from 2006 to 2008.

5.1.3 Screening of data

The collected data totalling 342 responses were duly checked and cleaned for consistency and treated where necessary. The consistency checks was conducted to identify data that are out of range, logically inconsistent, or have extreme values

(Malhotra, 2007). There were only a few cases that required the treatment for unsatisfactory responses due to the ambiguous answers given. Of the 342 completed questionnaires that were returned, two cases had gross missing values and they were omitted from further analysis. As such, this data preparation step trimmed the final number of responses for statistical analysis to 340. Subsequently, the raw data for these 340 cases were converted into a form suitable for statistical analysis.

5.2 Demographics of the respondents

Table 5.1 summarises the demographic characteristics of the respondents. The respondents were mostly the female employees (52.1%) compared to the male respondents at 47.9 percent. Majority of the respondents were between the age groups of 26 and 45, and they had Bachelor (66.2%) or Master (17.1%) degrees. About 42 percent of the respondents were from the middle management group while 49.7 percent of them were the executives. The respondents earned a monthly income ranging from less than RM3000 to more than RM9001. About 75 percent of the respondents have worked 20 years or less in their respective organizations with a majority of 37.4 percent having less than five years of tenure. In terms of ethnic group, 83.5 percent of them were Malays, 9.7 percent Chinese, 5.3 percent Indians, and the remaining 1.5 percent of them from other minor ethnic groups.

Additionally, there is an interesting phenomenon on age from the computed demographic statistics. Majority (66.4%) of the respondents was below the age of 40 and these are the identified talents in the GLC organizations. This could indicate that the GLC have taken cognizance of the importance in sourcing and grooming younger

Malaysians as future leaders. The Malaysian Government has in recent years identified and recruited talented young graduates to take on challenging national projects and functions such as the Bio Tech Corporation and the Talent Corp Berhad. A recent case on the focus for young talents in Malaysia is the appointment of the 37 years old Cambridge qualified chartered accountant as CEO of Talent Corporation Malaysia Berhad (Starbizweek, 2011). He is being tasked with wooing and retaining the right talents in Malaysia.

5.3 Data analyses

The analysis was conducted using PASW 18 (SPSS 18, 2010) and structural equation modelling (SEM) through AMOS 18 (Arbuckle, 2010). SEM is a multivariate technique used to analyse the covariance of observations and examine a series of dependence relationships simultaneously (Hair, Black, Babin, Anderson & Tatham, 2006). Descriptive statistics of means, standard deviations, alpha coefficients, and correlation coefficients of the measuring instruments' scales were used to analyse the data. The results are reported in Table 5.2 and Table 5.3.

5.3.1 Reliability

The internal reliabilities of each scale were obtained so as to establish the extent to which the latent variables are internally consistent. If the Cronbach's alpha coefficients of the measures are reliable, they would yield consistent results (Malhotra, 2007; Clark & Watson, 1995). According to Malhotra (2007), coefficient alphas of more than .6 would indicate satisfactory internal reliabilities.

Table 5.1
Demographic Characteristics of the Respondents

	n	%
Gender		
Male	163	47.9
Female	177	52.1
Total	340	100.0
Ethnic Group		
Malay	284	83.5
Chinese	33	9.7
Indian	18	5.3
Others	5	1.5
Total	340	100.0
Age		
Below 25 years old	22	6.5
26 – 30 years old	70	20.6
31 – 35 years old	73	21.5
36 – 40 years old	64	18.8
41 – 45 years old	59	17.4
46 years and above	52	15.3
Total	340	100.0
Highest level of Education		
A level / Diploma	35	10.3
Bachelor degree	225	66.2
Masters degree	58	17.1
Doctoral degree	2	0.6
Others	20	5.9
Total	340	100.0
Monthly Income		
RM3, 000 or less	64	18.8
RM3, 001 – RM5, 000	103	30.3
RM5, 001 – RM7, 000	47	13.8
RM7, 001 – RM9, 000	37	10.9
RM9, 001 or more	89	26.2
Total	340	100.0
Current designation		
Top Management (e.g. CEO / President)	1	0.3
Middle Management (e.g. V.P. / Sr. Manager / Manager)	143	42.1
Executive	169	49.7
Others	27	7.9
Total	340	100.0
Tenure in current organisation		
5 years and less	127	37.4
6-10 years	69	20.3
11-15 years	57	16.8
16-20 years	41	12.1
21-25 years	25	7.4
26-30 years	18	5.3
31-35 years	2	0.6
36 years and above	1	0.3
Total	340	100.0

Table 5.2 summarises the Cronbach's alphas of the six research constructs. They have all exceeded the threshold of .6 indicating satisfactory internal consistency for each of them. Although the Cronbach's alpha coefficient for intention to stay ($\alpha = .643$) was slightly lower than .70 as suggested by Nunnally and Bernstein (1994), they are acceptable according to Hair et al. (2006) and Malhotra (2007). Appendix B provides more details of the internal reliability of the six construct.

Table 5.2

Cronbach's Alpha Measures for the Six Constructs

Construct	Cronbach's Alpha
Psychological Empowerment (PE)	.92
Job Engagement (JE)	.72
Organization Engagement (OE)	.77
Job Satisfaction (JS)	.74
Intention to stay (ITS)	.64
Dedication (D)	.93

5.3.2 Correlations between the constructs

Constructs, as explained by Hair et al. (2006), are the unobservable or latent factors that are represented by a variate that consists of multiple variables. Constructs can be exogenous or endogenous. In this research, psychological empowerment (PE) is the exogenous construct, the latent multi-item equivalent of an independent variable. Job engagement (JE), organization engagement (OE) and job satisfaction (JS) that were the mediators in this study also alternate their role as exogenous and endogenous constructs. Intention to stay (ITS) and dedication (D) are the endogenous constructs.

The authors explained that endogenous constructs are the latent multi-item equivalent of dependent variables.

The Pearson product-moment correlation coefficients showed the linear relationships between the variables. Cohen (1988) advocates a minimum coefficient of .30 for the purpose of practical significance of the correlation coefficients. Table 5.3 summarises the correlation matrix for PE, JE, OE, JS, ITS and D. The results showed significant correlations between them at $\rho \leq .01$ and $\rho \leq .05$. All these results affirmed the propositions that there are positive relationships among the six research constructs. As the correlation coefficients between the six variables were above .30, they justify the application of factor analysis in this study (Cohen, 1988; Hair et al., 2006).

Table 5.3
Means, Standard Deviations (SD), Skewness, Correlation Matrix and Reliability of the Constructs

Variables	Mean	SD	Skewness	1	2	3	4	5	6
1. PE	5.43	1.02	-0.401	(.92)					
2. JE	3.83	0.84	-0.548	.499*	(.72)				
3. OE	3.81	0.79	-0.396	.515*	.521*	(.71)			
4. JS	3.98	0.79	-0.739	.539*	.425**	.600*	(.74)		
5. ITS	3.60	1.05	-0.448	.376**	.319**	.449*	.607*	(.64)	
6. D	5.55	1.20	-0.772	.672*	.532*	.546*	.595*	.438*	(.93)

Note Correlation is significant at * $\rho \leq .01$; ** $\rho \leq .05$
(All are in three decimal points to show the actual value computed)
PE = psychological empowerment; JE = job engagement; OE = organization engagement;
JS = job satisfaction; ITS = intention to stay; D = dedication
Cronbach's alpha reliabilities for the variables are provided in parenthesis

Through Table 5.3, it is also interesting to find that PE has the highest significant correlation with D at .67 compared to JS and ITS at .54 and .38 respectively. Results in the table also show that JS had the highest significant correlation with OE compared to PE and JE. Similarly, among other constructs, ITS displayed the highest significant correlation with JS at .61. D is noted to have moderate significant correlation with JE, OE and JS at .53, .55 and .60 respectively. D had the lowest significant correlation with ITS at .44.

5.3.3 Factor Analysis

All the items that describe each of the measures were factor analysed to define the underlying structure among the variables before proceeding with CFA. Accordingly, for factor analysis to be appropriate, the variables must show interrelationships. The six main scales of the research were subjected to the principal component analysis with varimax rotation to examine their unidimensionality as well as to determine the structure of the components. Unidimensionality is important to ensure that each measured variable relates to a single construct only. All cross-loadings are assumed to be zero in a unidimensional construct; otherwise the construct validity would be lacking. Unidimensionality measures must exist to ascertain that each set of measured variable (indicators) has only one underlying construct (Hair et al., 2006).

Principal component analysis is used because it takes into account the total variance in the data (Malhotra, 2007). The author advocates that principal component analysis helps to summarize most of the variance in a minimum number of factors for prediction purposes. Initial analysis showed that the validity of the six scales was supported as indicated by the percentage of variance exceeding 50 percent and the factor loadings of numerous items within each scale were more than .5. Factor loadings of ± .30 to ± .40 are minimally acceptable in social science; however, values greater than ± .50 are considered necessary for practical significance (Hair et al., 2006)

Communalities is also analysed to determine if the variables meet acceptable levels of explanation. Communalities represent the average amount of variation among the measured or indicator variables explained by the measurement models (Hair et al., 2006). It is also the total amount of variance an original variable shares with other variables in the analysis. According to the authors, the index of the communalities indicates the amount of variance in a particular variable that is accounted for by the factor solution. Although there is no statistical guide of what is high or low communalities, Hair et al. (2006) suggest the level of .50 for practical consideration.

Table 5.4

Summary of the Communalities of the Six Variables

The variables	Initial value	Extraction*
Psychological Empowerment (PE)	1.000	.618
Job Engagement (JE)	1.000	.499
Organization Engagement (OE)	1.000	.624
Job Satisfaction (JS)	1.000	.674
Intention to stay (ITS)	1.000	.460
Dedication (D)	1.000	.686

Extraction method: Principal component analysis
* The values are presented in three decimal points to show the actual figures produced.

In this research, the communalities among the variables are shown in Table 5.4. The Table 5.4 showed that all variables with the exception of JE (.499) and ITS (.460) exceeded the practical requirement of .50 to indicate having sufficient explanation. Despite the communalities of JE and ITS were just about .50, this level was acceptable according to Hair et al.'s (2006) suggested minimum range between .30 and .40. Hence, it is plausible that both variables JE and ITS met acceptable levels of explanation in the factor analysis.

Table 5.5

Summary of the KMO and Bartlett's Test Results for the Six Variables

Construct	**Kaiser-Meyer-Olkin Measure of Sampling Adequacy**	**Bartlett's Test of Sphericity**	
		Approx. Chi-square	**Sig** ($\rho < .05$)
PE	.88	3175.41	.00
JE	.77	504.80	.00
OE	.79	565.38	.00
JS	.69	240.84	.00
ITS	.56	199.13	.00
D	.87	1433.74	.00

Note. PE = psychological empowerment; JE = job engagement; OE = organization engagement; JS = job satisfaction; ITS = intention to stay; D= dedication.

Table 5.5 shows that the Kaiser-Meyer-Olkin (KMO) or the measure of sampling adequacy for PE, JE, OE, JS, ITS and D were larger than .50. This revealed that the correlations between pairs of variables such as PE, TE and TO can be explained by other variables in the research model (Malhotra, 2007). The KMO is an index that was used to examine the appropriateness of factor analysis for the data in this study. It is also a statistics that indicates the proportion of variance in the variables that might be caused by underlying factors.

Malhotra (2007) advocated that high values between 0.5 and 1.0 indicate that the factor analysis is appropriately used in the intended study. Therefore, the generated KMO values of .88, .77, .79, .69, .56 and .87 for the six constructs showed that the data has sufficient correlations to justify the application of factor analysis. The findings also assumed some degree of multicollinearity that represents the degree to which any variable's effect can be predicted or accounted for by the other variables in the analyses. According to Hair et al. (2006), some degree of multicollinearity is desirable because the objective of the analysis is to identify interrelated sets of variables (Hair et al., 2006).

Bartlett's test of sphericity is a statistical test for the overall significance of correlations within a correlation matrix (Hair et al., 2006). Malhotra (2007) explains it as a test statistics to examine the hypothesis that the variables are uncorrelated in the population and therefore unsuitable for structure detection. In this study, the chi-square readings for psychological empowerment (PE), job engagement (JE), organization engagement (OE), job satisfaction (JS), intention to stay (ITS) and dedication (D) are large as shown in Table 5.5. As such, the null hypothesis that the variables were uncorrelated in the study was rejected and that the appropriateness of factor analysis accepted. These six constructs also generated significant readings at .000 that were < .005, meaning that the null hypothesis for the six constructs was rejected and there were relationships among the variables. A statistically significant Bartlett's test of sphericity ($\rho < .05$) indicated that sufficient correlations exist among the variables to proceed further (Hair et al., 2006). Since Bartlett's test of sphericity was large and significant, and KMO measures were greater than .5, factorability was assumed for the data in this study.

5.3.4 Confirmatory Factor Analysis (CFA)

Based on the results from EFA that determined the underlying dimensions of the measurement scale, the next step was to use the CFA to test the measurement model in this study. The purpose of computing CFA is to assess the degree to which the data meet the expected structure. It also tests how well the measured items that represent the constructs define the relationships between the latent variables and their indicator variables (Hair et al., 2006). Thus, the CFA tests the measurement theory by providing evidence on the validity of each measure based on the model's overall fit. According to the authors, an advantage of using the CFA is to test the conceptually grounded theory that explains how the different items represent the measures. In addition, the CFA helps to confirm if a theoretical measurement model is valid. The relationships between observed and latent variables that are shown by the factor loadings or regression weights in AMOS would describe the extent to which a given indicator is able to measure the validity of the variable. The measurement error would explain the extent to which the latent factor does not explain the measured variables.

In assessing CFA, the AMOS software was used as it will automatically fix one of the factor loading estimates to 1. Hair et al. (2006) advocate for an over-identified model so that the model will have more unique covariance and variance terms than the parameters to be estimated. This is the desired state for CFA and SEM models. However, the authors suggested the three indicator rule whereby all factors in a congeneric model must have at least three significant indicators to achieve satisfaction condition for identification. In this study, psychological empowerment, job engagement, organization engagement and dedication were over identified models while job satisfaction and intention to stay were saturated or just-identified models as shown in Tables 5.6 and 5.7 since both the variables had just three indicators.

Table 5.6

Initial Identification of the Six Constructs

Construct	No. of significant indicators	No. of unique covariance & variance terms	No. of parameters to be estimated	DF	Remark
PE	4	14	12	2	Over-identified
JE	5	20	15	5	Over-identified
OE	5	20	15	5	Over-identified
JS	3	9	9	0	Just-identified
ITS	3	9	9	0	Just-identified
D	5	20	15	5	Over-identified

Note. PE = psychological empowerment; JE = job engagement; OE = organization engagement; JS = job satisfaction; ITS = intention to stay; D= dedication.

In general, the research constructs satisfy the congeneric principle whereby all the measured items are allowed to load on only one construct each. The research constructs also met the reflective measurement model's requirements specified by Hair et al. (2006) where all constructs must have at least three item indicators to enable the constructs to be statistically identified. The latent constructs in the reflective measurement model may comprise of both the measured variables as well as the measurement errors brought about by the constructs' inability to fully explain the measures.

Table 5.7

Identification of the Six Constructs after Minor Modifications for better Measurement Fit

Construct	No. of distinct sample moments	No. of minor modifications made	No. of distinct parameters to be estimated	DF	Remark
PE	14	1 (e2<->e4)	13	1	Over-identified
JE	20	2	17	3	Over-identified
OE	20	-	15	5	Over-identified
JS	9	-	9	0	Just-identified
ITS	9	-	9	0	Just-identified
D	20	3	18	2	Over-identified

Note. PE = psychological empowerment; JE = job engagement; OE = organization engagement; JS = job satisfaction; ITS = intention to stay; D= dedication.

5.3.5 Assessment of the Validity of the Measurement Model and Model Fit

Typically, a complete SEM model comprises of two models; namely the measurement and structural models. The measurement model represents specification of the measurement theory and it shows how constructs are operationalised by sets of measured variables. The structural model shows how constructs are associated with each other, often with multiple dependence relationships. The measurement model that is tested by using only CFA assumes that all constructs are correlated with one another (correlational relationships).

The SEM model in this study was estimated to provide empirical measures for the relationships among variables and constructs represented by the measurement theory. It helped to estimate how well the theory fits the data. The measurement model for each of the construct emphasised the relationship between the latent construct and measured variables. The structural model however involved specifying the nature and magnitude of the structural relationships between latent constructs. The model is formalised in a path diagram to obtain an empirical estimation of the strength of each path (relationship) by using only a correlation or covariance matrix as input (Hair et al., 2006).

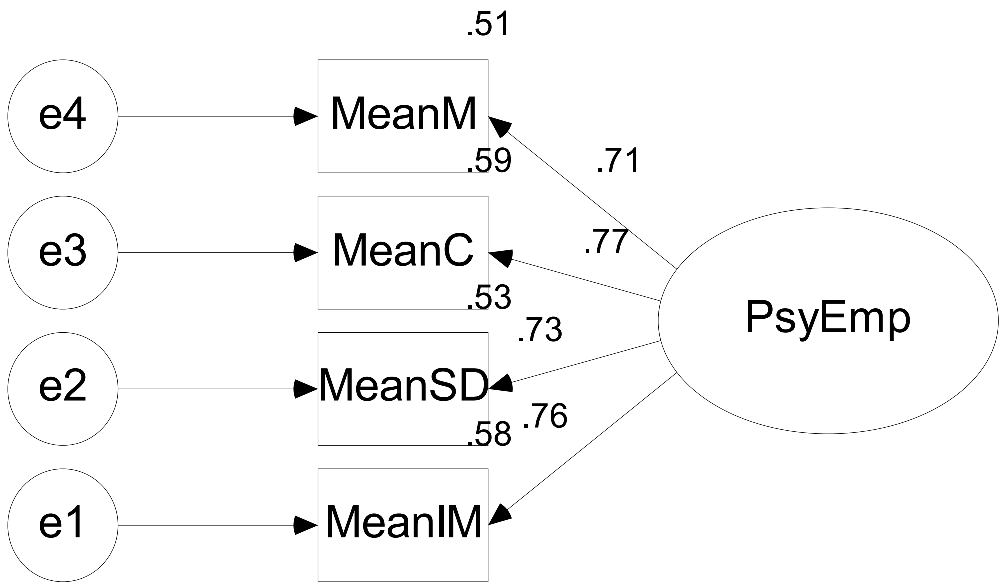
The standardised estimates of the measurement models as shown in Figures 5.1 to 5.6 and the structural model for the research framework as drawn in Figure 3.1 were based on the sound theoretical work on psychological empowerment (Spreitzer, 1995), employee engagement and job satisfaction (Saks, 2006), job satisfaction (Mowday et al., 1979), dedication (Schaufeli et al., 2001; Kahn, 1990) and intention to stay (Shore and Martin, 1989). With the large data and the measurement models specified (Figures 5.1 to 5.6), the validity and “fitness” of the measurement models were subsequently analysed. According to Hair et al. (2006), the validity of measurement models depends on the goodness-of-fit and specific evidence of construct validity.

Construct validity refers to the extent to which the set of measured variables in the study actually represents the theoretical latent construct they are designed to measure (Hair et al., 2006). This means that construct validity deals with the accuracy of the measurement. On the other hand, goodness-of fit (GOF) indicates how well the specified model reproduces the covariance matrix among the indicator items; it refers to the similarity of the observed and estimated covariance matrices. Byrne (2010) further explains that the GOF indicates the extent to which a hypothesised model fits or adequately described the sample data.

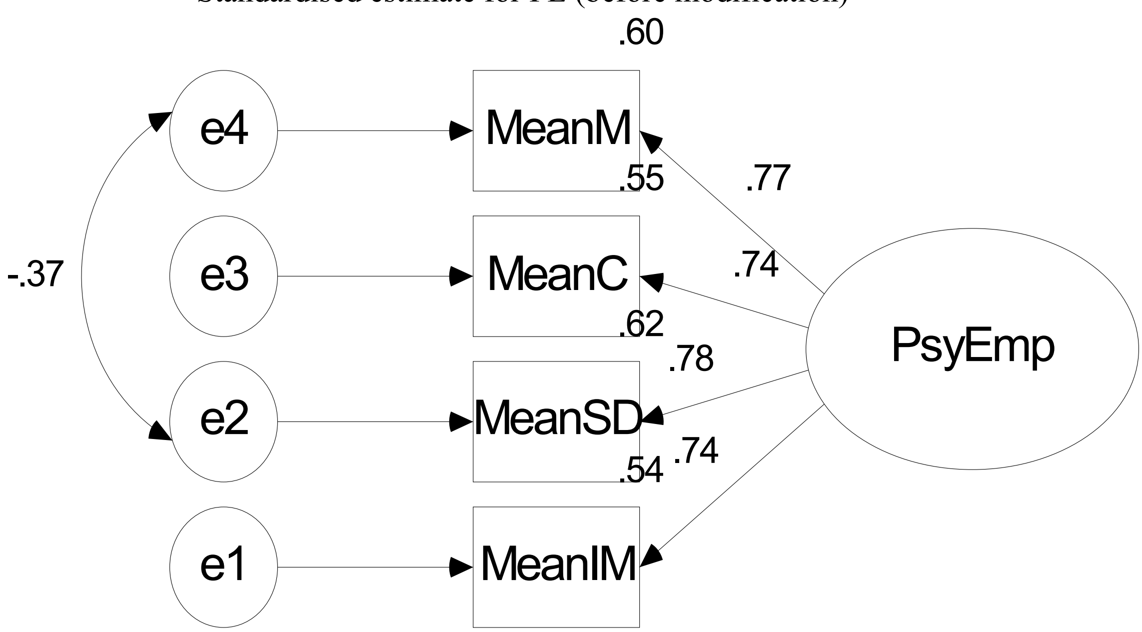
Measurement Model of the Psychological Empowerment (PE)

Validity refers to the "scientific utility of a measuring instrument, broadly stable in terms of how well it measures what it purports to measure" (Nunnally & Berstein, 1994, p.83). Figure 5.1 shows that in terms of construct validity, PE has convergent validity whereby the items within the construct share a high proportion of common variance. The initial variance extracted or squared multiple correlation of PE ranged from 51 percent for meaning (MeanM) to 59 percent for competence (MeanC). These values exceeded the 50 percent rule of thumb for variance extracted for adequate convergence as advocated by Hair et al. (2006). The convergent validity is also indicated by the significant standardised loading estimates of .71, .77, .73 and .76 before modification, and .77, .74, .78 and .74 after one modification (e2<->e4) as shown in Figure 5.1. The modified measurement model for PE also met the rule of thumb that factor loadings be .5 or higher (Hair et al., 2006).

The PE variable was subjected to one modification to improve its GOF as revealed in Table 5.8. The factor loadings disclose the degree of relationships between the latent constructs, PE, and the respective measured variables. The high loadings on a factor (construct) reveal that they converge on some common points and that more of the variance in the measure is explained variance rather than an error variance (Byrne, 2010). Figure 5.1 showed that the PE factor had adequate convergence with the



Standardised estimate for PE (before modification)



Standardised estimate for PE after 1 modification (e2<->e4)

Figure 5.1 **Measurement Model of Psychological Empowerment.**
*Note.*PsyEmp = psychological empowerment.

variance extracted values of .51, .59, .53 and .58 before modification and .60, .55, .62 and .54 after just one modification (e2<->e4). The improved variance extracted for MeanM and MeanSD indicate that 60% of the variance of MeanM is accounted for by

PE compared to 51% before the modification, while the remaining 40% is attributed to an error term e4. Similarly, 62% of the variance in MeanSD is accounted for by PE after the modification compared to 53% before it, while the remaining 38% is attributed to the error term, e2. Besides the factor loading and variance extracted, the convergent validity of PE is also supported by the internal reliability of .92 as shown in Table 5.2. It therefore met the requirement of .7 or higher for good (adequate) reliability as suggested by Nunnally and Bernstein (1974). The higher construct reliability revealed that the measures of PE all consistently represented the same latent construct.

Table 5.8

Comparison of the GOF values for the PE Measurement Model

The GOF	**The Initial GOF values**	**Remark**	**After one M.I. GOF values[a]**	**Remark**
cmin	14.33	Large χ^2 value	0.94	Better fit
DF	2	-	1	-
ρ	.001	<.05(significant – bad fit)	.33	>.05 (not significant means good fit)
cmin / DF	7.16	> 2 (bad fit)	0.94	< 2 (meets the rule of thumb)
CFI	.98	>.90	1.00	Perfect fit
NFI	.97	>.90	.998[a]	> .90 (Good fit)
RMSEA	.14	> .06 (high bad fit)	.000	< .06 (meets the rule of thumb)

Note. M.I = modification index

[a] The GOF values are reported in 3 decimal points to show the actual change in value before and after M.I.

The PE factor also fulfilled the discriminant validity requirements. This was shown by the higher variance extracted PE estimates than the squared correlation estimates between PE and the other constructs indicated in Table 5.3. For example, variances extracted as indicated in Figure 5.1 were greater than the squared correlation coefficients of the PE-Dedication at .45 (i.e. the square of .672). The congeneric measurement model of PE also supported the discriminant validity because it did not contain any cross-loadings either among the measured variables or among the error items. As PE is a well researched area as explained in Chapter 2, Spreitzer's (1995) PE items were consistent with the definition of the construct. Face validity was evident as the conceptual definitions matched well with each of the items. The face validity of PE was complemented by the nomological validity as the correlations among the six constructs in the measurement theory made sense and supported the hypotheses that these constructs were positively related to one another. These, in turn, supported the validity of the theoretical framework.

In terms of model fit, Hair et al. (2006) do not recommend researchers to free the covariance terms as it can violate the principles of good measurement. However, since the original badness-of-fit (RMSEA) value for the PE measurement model at .14 (see Table 5.8) was greater than .08 or less as suggested by the authors, a modification index was introduced in the model. The outcome was that it reduced the RMSEA value to .00. In this PE measurement model, the modification index (M.I) of e2<->e4 was chosen because its M.I. of 7.43 exceeded the threshold value of 4.0 as recommended by Hair et al. (2006). The authors believe that a M.I. of 4.0 and above could improve the model fit significantly by estimating the corresponding path. The authors noted that a M.I. is calculated for every possible relationship that is not free to be estimated. Each M.I. shows how much the overall model χ^2 value would be reduced by freeing that single path. However, the authors suggested that any change for M.I. must be justified by theory so that it is consistent with the theoretical basis of

CFA and SEM in general. Byrne (2010) also explains that by adding a M.I. value, it means freeing a parameter that could result in a drop of the overall chi-square value where the model would be re-estimated.

Table 5.8 and Figure 5.1 also showed that the correlation between e2 and e4 was sound because when an individual finds meaning or meaningfulness in what one does, it enhances one's self-determination. The resultant par change of -0.37 was more than the estimated par change of -0.071. Even the cmin or χ^2 and the probability values improved from 14.33 and .001 to 0.94 and .33. This is crucial that the theory be supported by this test. Byrne (2010) recommends a smaller χ^2 value with a corresponding larger ρ value to indicate the statistically non-significant difference between the matrices. The CFI value had improved from .975 to 1.000 (perfect fit). The RMSEA and the CFI for the modified PE measurement model suggest a good model fit. Using a Type 1 error rate of 0.01, the model had an insignificant $\chi^2$with $\rho = .332$ that is $\rho > .05$ supporting the good fit. The GOF values for the PE measurement model are as indicated in Table 5.8.

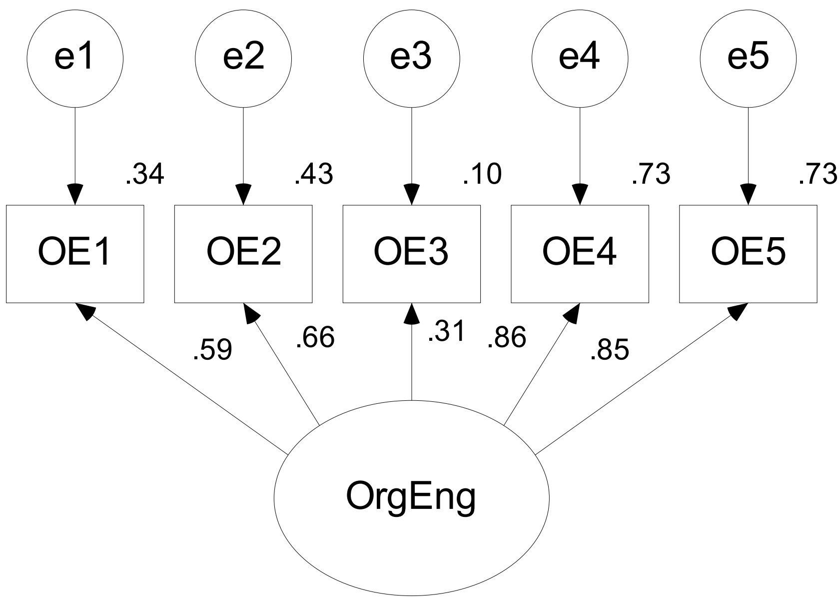
PE was an over identified measurement model as it had two degrees of freedom before the modification and one degree of freedom after the modification through the covariance of e2<->e4 for better fit. Identification looks at whether enough information exists to identify a solution to a set of structural equations. The degree of identification is characterised by the degrees of freedom a model has after all the parameters to be estimated are specified (Hair et al., 2006). In this case, the PE measurement model had more unique values in the covariance matrix [4(4+1)/2 = 10] than the number of parameters to be estimated [4 regression paths / factor loadings + 4 error variance estimates] resulting in a possible unique solution. The error variance estimates showed by the measurement error refer to the extent to which the latent factor does not explain the measured variables (Hair et al., 2006). The authors also suggested that measurement error is explicitly modelled to each manifest variable to derive unbiased estimates for the relationships between the latent constructs.

Measurement Model of the Organization Engagement (OE)

The OE was the only construct that had the GFI and AGFI values as it did not require any modification. The values generated were .99 for GFI and .97 for AGFI. This was theoretically supported although its value extracted or squared multiple correlation coefficients varied between 10 percent for OE3 and 73 percent for OE4 and OE5 as indicated in Figure 5.2. Except for OE3 with a factor loading of .31, the rest exceeded .5 as by Hair et al. (2006). The standardised AMOS graphic output for OE indicated that OE4 was the best predictor of OE with the regression coefficient of .86 followed by OE5 at .85, OE2 at .66, OE1 at .59, and lastly OE3 at .31. Perhaps OE3 was a negatively worded item.

The convergent validity of OE was supported by the .77 internal reliability of the construct (see Table 5.2) that met the rule of thumb of .7 or higher for adequate reliability (Nunnally & Bernstein, 1994). This moderately high construct reliability means that the measures of OE consistently represented the same latent construct.

The congeneric OE measurement model supported the discriminant validity as it did not contain any cross-loadings either among the measured variables or among the error items. Face validity for OE was evident based on matching the conceptual definitions and the wordings of each item as suggested by Saks (2006). The positive relationships among the six constructs supported the nomological validity of OE. The construct validity of OE was complemented by the high GOF values for OE as shown in Table 5.9.



Standardised estimate (no need modification)

Figure 5.2 **Measurement Model of Organization Engagement.**
Note. OrgEng = organization engagement.

The results of the goodness-of-fit (GOF) for OE: CFI at .99, ρ-value at .13 that was greater than .05 indicating a non-significant value, and the cmin/df value of 1.72 that met the rule of thumb for values below 2.0 revealed that the OE measurement model had achieved a good fit. The χ^2goodness-of-fit statistics indicated that the observed covariance matrix matched the estimated covariance matrix within the sampling variance. In addiiton, the actual RMSEA value at .046 that was approximately .05, was below the general guideline of .08 as suggested by Hair et al. (2006).

Table 5.9

The Goodness-of-Fit values for the OE Measurement Model

The GOF	The GOF values	Remark
cmin	8.62	Relatively small value
DF	5	-
ρ	.13 (.125[a])	> .05 (not significant)
cmin / DF	1.72	< 2.00 (met the rule of thumb)
CFI	.99	> .9 (met the rule of thumb)
NFI	.99	> .9 (met the rule of thumb)
RMSEA	.05 (.046[a])	< .06 (met the rule of thumb)
GFI	.99	> .90 (met the rule of thumb)
AGFI	.97	> .90 (met the rule of thumb)

[a] Actual values in three decimal points

This model did not need any modification. At a Type 1 error rate of 0.01, the model had an insignificant χ^2 test of ρ equals .125 (i.e. $\rho \geq .05$). With a good fit and high values for GFI and AGFI, OE was the only congeneric measurement model in the research framework that did not need any modification to improve the model fit. This means that the OE measurement model was sufficiently constrained to represent good measurement properties. This also means that all cross-loadings were constrained to zero and there was no covariance within the construct error variances. As such, this model had construct validity and consistent with good measurement practice (Hair et al., 2006). This finding was also supported as shown in Table 5.10 because all the standardised residual covariances for OE were below the threshold of ±2.5 thereby indicating there was no problem with the measures.

Table 5.10

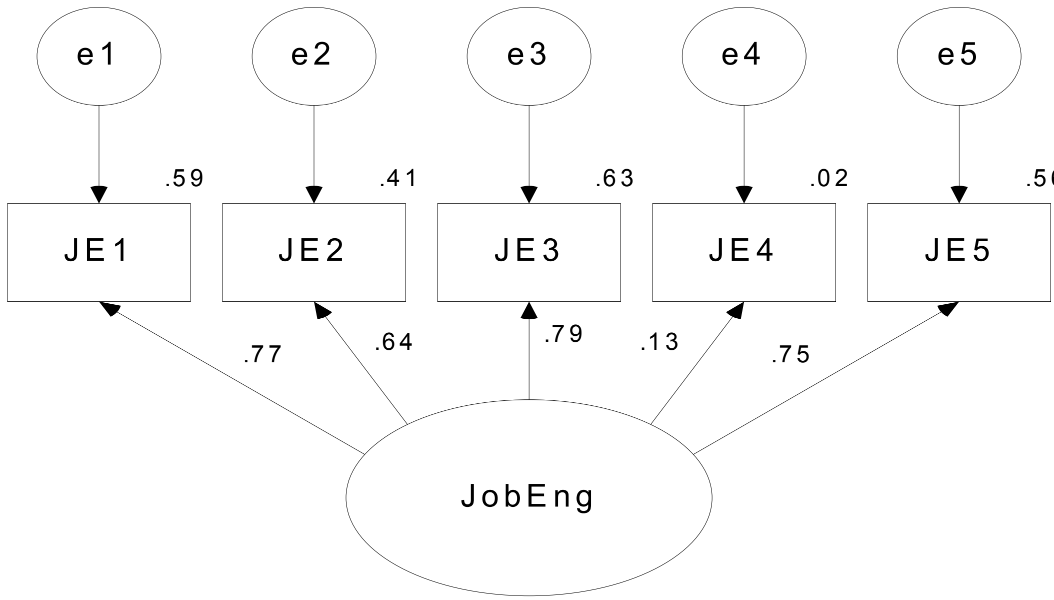
Standardised Residual Covariances for OE

	OE5	OE4	OE3	OE2	OE1
OE5	0.000				
OE4	0.088	0.000			
OE3	0.254	-0.313	0.000		
OE2	-0.189	-0.149	1.001	0.000	
OE1	-0.187	-0.029	-1.079	0.909	0.000

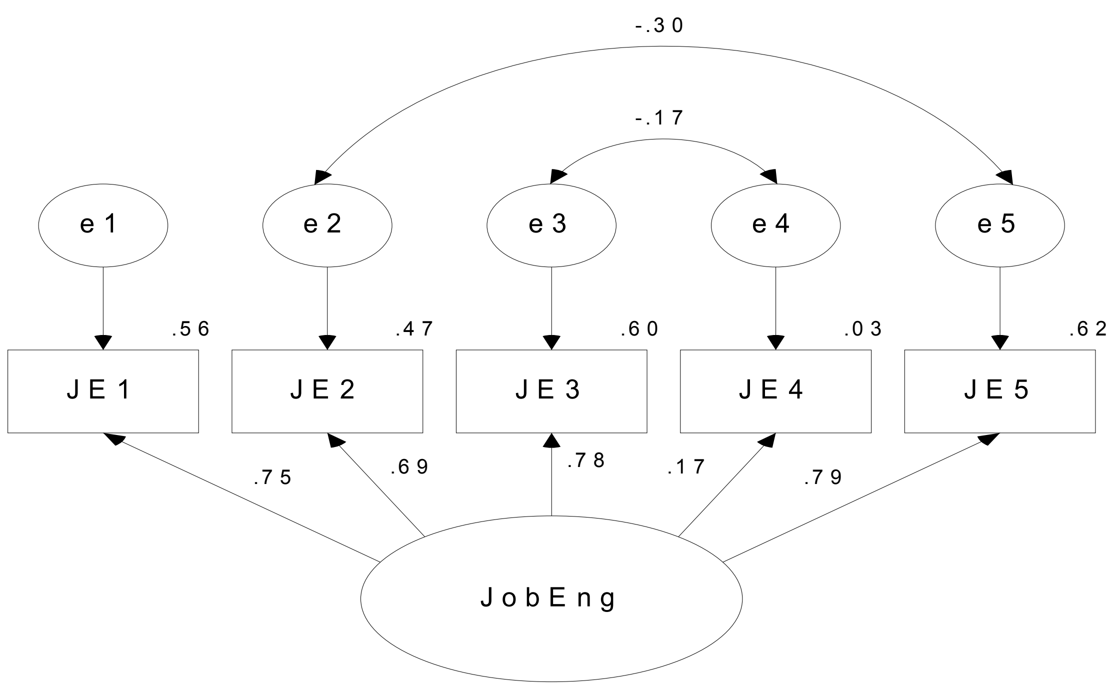
* The values are reported in three decimal points to show the actual values generated and reflect the actual outcome.

Measurement Model of Job Engagement (JE)

The analysis of JE is similar to OE in that the construct was theoretically supported (Saks, 2006) although its items' value extracted (before modification) were between two percent for JE4 and 59 percent for JE1 as noted in Figure 5.3. JE4 was a reversed question and this could explain its low value extracted value. Except for the reversed item of JE4 at .13 (before modification), the factor loadings for the rest generally exceeded the rule of thumb of .5 or higher (Hair et al., 2006). The convergent validity of JE was supported by the internal reliability of the construct at .72 (see Table 5.2) that met the rule of thumb of .7 or higher for adequate reliabilities (Nunnally & Bernstein, 1994). This high construct validity means that the measures of JE consistently represented the same latent construct. The congeneric measurement model of JE did not have any cross-loadings either among the measured variables or among the error items. Hence, the JE measurement model supported the discriminant validity.



Standardised estimates (before modification)



Standardised estimates for JE after 2 modifications

***Figure* 5.3 Measurement Model of Job Engagement.**
Note. JobEng = job engagement.

As noted by Saks (2006), JE has face validity as the conceptual definition of JE explains the item wordings. Positive relationships among the six constructs generated the nomological validity for JE. The above findings that showed JE had acceptable construct validity, was supported by its internal reliability of .72. The JE measurement model was subjected to two minor modifications (e3 <-> e4 and e2 <-> e5) to improve its model fit. These two modifications indexes (M.I.) were chosen because their M.I. values at 6.742 and 8.006 were greater than the recommended guideline of 4.0. The correlation between e2 and e5 was particularly sound because when one is so into the job (JE2), one is highly engaged (JE5).

The RMSEA and CFI values for the modified JE measurement model suggested a good fit. In general, an acceptable model would have values greater than .90 for GFI, CFI, TLI as well as a value of less than .08 for RMSEA (Hair et al., 2006). In this case, the value of CFI improved from .97 to 1.00 while the value of RMSEA improved from .10 to .00. Besides, Hu and Bentler (1999) recommend the cut-off value of .95 for CFI and TLI for a well fitted model. The authors also advocate the cut off value of .06 for RMSEA to support a relatively good fit between the hypothesised model and the observed data. In addition, Hair et al. (2006) suggests that the acceptable ratio for χ^2/df value should be less than 3.0 However, since the results showed 0.97 which was less than 2.0, it indicated a good fit. Using a Type 1 error rate of 0.01, the model had an insignificant χ^2 with ρ equals .41. This was greater than .05 thus supporting the outcome that the revised JE measurement model had achieved a good fit. A comparison of its goodness-of fit (GOF) values before and after modification is shown in Table 5.11.

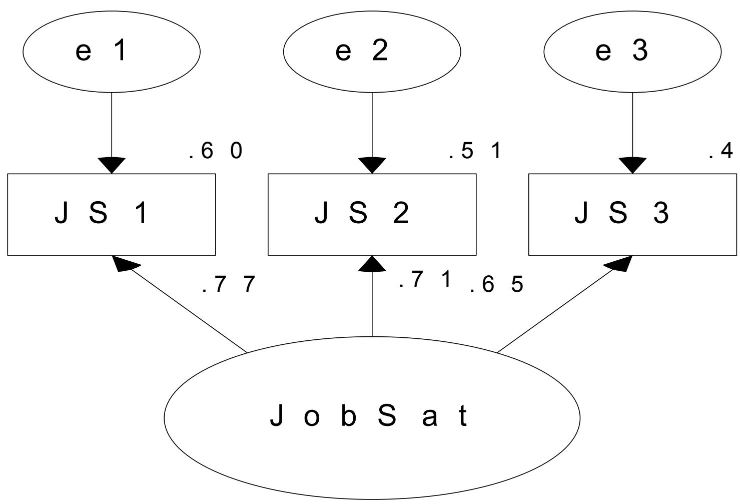
Table 5.11

Comparison of GOF values for the JE Measurement Model

The GOF	The initial GOF values	Remark	The after modification GOF values	Remark
cmin	22.58	Value rather large	2.91	Better value
DF	5	-	3	-
ρ	.00	< .05 (significant = not good fit)	.41	> .05 (not significant = good fit)
cmin / DF	4.52	> 2.0 (same)	0.97	< 2.0 (good fit)
CFI	.97	> .9 (met the rule of thumb)	1.00	perfect fit
NFI	.96	> .9 (same)	.94	> .9 (met the rule of thumb)
RMSEA	.1	> .06 (not good fit)	.00	< .06 (same)

Measurement Model of Job Satisfaction (JS)

The JS construct in this research had three items that were adopted from Saks (2006). As such, it was a just-identified or saturated model with 0 degree of freedom without any recommended statistical modification index. This construct had the value extracted values that ranged between 42 percent for JS3 and 60 percent for JS1. Although the value extracted value for JS3 was slightly below the 50 percent suggestion of Hair et al. (2006), this moderate value was acceptable theoretically as it had content validity. Additionally, there is a need to meet the minimal number of items for statistical identification requirements (Hair et al., 2006). As noted in Figure 5.4, factor loadings for the JS items at .77, .71 and .65 were above that advocated by Hair et al. The JS construct recorded an internal reliability of .74 (see Table 5.2) that exceeded the guideline of .7 or higher for adequate reliability as suggested by Nunnally and Bernstein (1994). This means that the measures of JS constantly represented the same latent construct and it supported the convergent validity. As this construct did not have any cross-loadings, the congeneric JS measurement model had discriminant validity. Face validity for JS was evident as its conceptual definitions matches with the meaning of the item wordings (Saks, 2006). The positive relationship of JS with the other five constructs indicated nomological validity. The goodness-of fit (GOF) values for the JS construct validity are as in Table 5.12.



Standardised estimates for JS (no modification required)

Figure 5.4 **The Measurement Model of Job Satisfaction.**
Note. JobSat = job satisfaction.

JS had the minimum required number of three items (indicators) for this construct. As explained, the three-items indicator was just-identified. This meant that the construct included just enough degrees of freedom to estimate the free parameters. According to Hair et al. (2006), a just-identified or saturated model with zero degrees of freedom has perfect fit as indicated by the NFI and CFI values of 1.00. As a result, the badness-of-fit or RMSEA was not computed. The just-identified model of JS can be indicated using the degrees of freedom equations as follows: DF = ½ [p(p+1)] – k where p is the total number of observed variables and k is the number of estimated (free) parameters (ibid, p.746). Therefore, the DF for JS was 3(3+1)/2 – 6 = 0. k for JS consists of three (3) factor loadings (regression paths) and three (3) error variances to be estimated totaling six (6) parameters. Accordingly, the χ^2 goodness-of-fit statstic for a saturated model is also 0. This being the case, the just-identified model does not test the theory as their fit was determined by the circumstance. Nevertheless, the JS measurement model is acceptable as there were other constructs in the research model that have more than three indicators (Hair et al., 2006).

Table 5.12

The Goodness-of-Fit values for JS Measurement Model

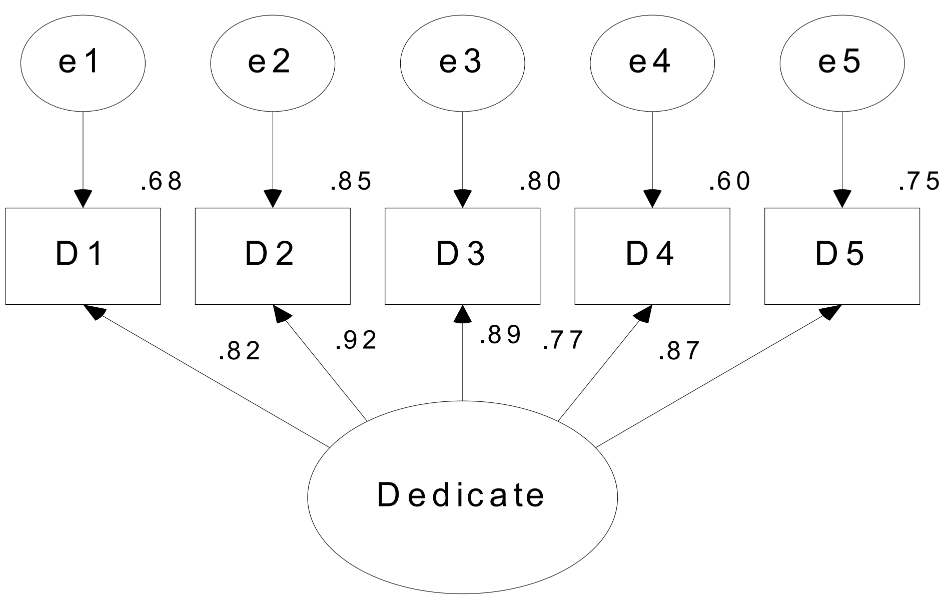
(no M.I. recommended)

The GOF	The GOF values	Remark
cmin	0.00	} no value
DF	0	} because
ρ	-	} it is a saturated
cmin / DF	-	} model
CFI	1.00	perfect fit
NFI	1.00	perfect fit
RMSEA	-	not computed

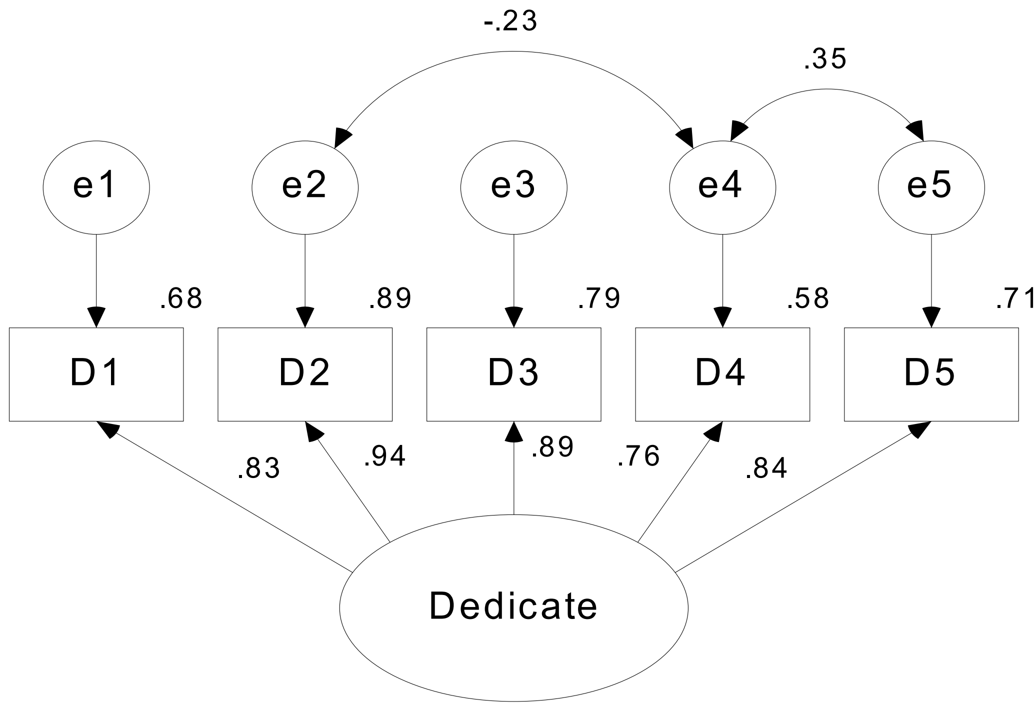
Note. M.I.= modification index

Measurement Model of Dedication (D)

In analysing the construct validity of Dedication, this construct had convergent validity as the items within the construct shared a relatively high proportion of common variance. The initial value extracted for Dedication were between 60 percent for D4 to 85 percent for D2, thus exceeding the 50 percent rule of thumb for acceptable value extracted (Hair et al., 2006). Figure 5.5 shows the convergent validity of Dedication as indicated by the significant standardised loading estimates of .82, .92, .89, .77 and .87 for each of the four items before modification and .83, .94, .89, .76 and .84 after two modifications (e4 <-> e5 and e2 <-> e4). The high loadings on Dedication indicated that the items converged on some common points and that more of the variance in the measure was explained variance rather than error variance. The convergent validity of Dedication was also supported by its internal reliability of .93 (see Table 5.2) that met the rule of thumb of .7 or higher for good (adequate) reliability as suggested by Nunnally and Bernstein (1994). This high construct reliability means that the measures of Dedication all consistently represented the same latent construct. As this construct did not have any cross-loadings, the congeneric Dedication measurement model had discriminant validity. The research of Schaufeli et al. (2002) has also supported the face validity of Dedication where the conceptual definition of Dedication matches with items' wordings.



Standardised estimates for Dedication (before modification)



Standardised estimates for Dedication
(After 2 modifications: e4<->e5 & e2<->e4)

Figure 5.5 **The Measurement Model of Dedication.**
Note. Dedicate= dedication.

The positive relationships among the six constructs indicated nomological validity for Dedication. The measurement model for Dedication was subjected to two minor modifications (e4 <-> e5 and e2 <-> e4) to improve model fit. The modification indexes (M.I.) of e4<->e5 and e2<->e4 were chosen as they were the most appropriate M.I. to improve the model significantly. The inclusion of the two modification indexes had reduced the χ^2 value tremendously from 59.68 to 5.93, resulting in improvement of the cmin/df from 11.94 to 1.98. The correlation between e4 and e5 was theoretically sound as pride (D4) occurs when there are meaning and purpose in what one does (D5). Similarly, when one finds the job inspiring (D2), it will bring about pride on the work that one does (D4). This after modified model resulted in the improved RMSEA value to .05 and the CFI value to .998 suggesting a good fit for the Dedication measurement model. At 99% confidence interval or a Type 1 error rate of 0.01, the modified model had an insignificant χ^2 test with ρ equals .12 indicating that the Dedication measurement model had achieved good fit. A comparison of its GOF values before and after modification is shown in Table 5.13.

Table 5.13

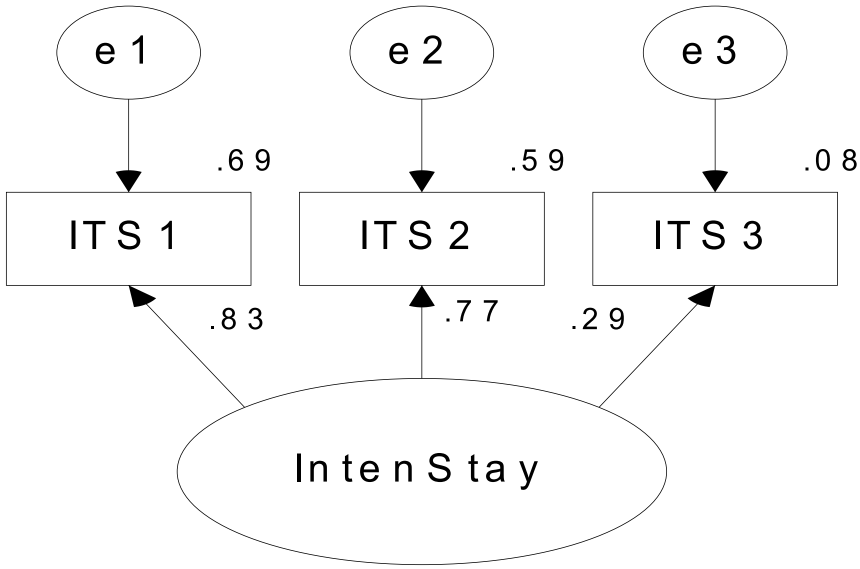
Comparison of GOF values for the Dedication Measurement Model

The GOF	The initial GOF values	Remark	The after modification GOF values	Remark
cmin	59.68	Value rather large	5.93	Better value
DF	5	-	3	-
ρ	.00	< .05 (significant = not good fit)	.12	> .05 (not significant = good fit)
cmin / DF	11.94	> 2.0 (same)	1.98	< 2.0 (good fit)
CFI	.96	> .9 (met the rule of thumb)	.998[a]	perfect fit
NFI	.96	> .9 (same)	.996[a]	> .9 (met the rule of thumb)
RMSEA	.18	> .06 (not good fit)	.054[a]	< .06 (same)

[a] These values are shown in three decimal points to reflect the actual value generated.

Measurement Model of Intention to Stay (ITS)

The ITS construct as with the JS construct in this research had three items adopted from Saks (2006). This just-identified or saturated model with 0 degree of freedom did not recommend any statistical modification. The construct recorded value extracted that ranged from eight percent for ITS3 to 69 percent for ITS1 as shown in Figure 5.6. ITS3 had low value extracted and factor loading because it was a reversed scored question. Except for ITS3, all the other value extracted and factor laodings for ITS passed the rule of thumb limit as suggested by Hair et al. (2006). The ITS construct produced a moderate internal reliability of 0.64 (see Table 5.2) indicating a relative consistent representation of the ITS measures for the same latent construct.



Standardised estimates (no modification required)

Figure 5.6 **The Measurement Model of Intention to Stay.**
Note. IntenStay = intention to stay.

As this congeneric ITS measurement model did not have any cross-loadings, it fulfilled the requirement for discriminant validity. This study concurs with Saks (2006) on the face validity for ITS as indicated by the similarity of meaning between the conceptual definition of ITS and the item wordings. Nomological validity for ITS was shown through the positive relationships among the six constructs. In terms of goodness-of-fit, this just-identified or saturated ITS measurement model with zero degrees of freedom indicated perfect fit as displayed by the CFI and NFI values of 1.00. This being the case, the badness-of-fit or RMSEA was not computed. The ITS measurement model had the GOF values as shown in Table 5.14.

Table 5.14

The Goodness-of-Fit values for ITS Measurement Model

The GOF	The GOF values	Remark
cmin	0.00	} no value
DF	0	} because
ρ	-	} it is a saturated
cmin / DF	-	} model
CFI	1.00	perfect fit
NFI	1.00	perfect fit
RMSEA	-	not computed

This model did not require any modification. From the computations for the standardised estimates, only OE3, JE4 and ITS3 indicated path estimates below .50. Although they became target for deletion from the model, the items were retained because of content validity (for OE3 and JE4) and the need to meet the minimal number of items per factor consideration or statistical identification requirements (ITS3). This decision is based on the importance of consideration for theory in making model modifications as CFA test focuses on measurement theory.

The criteria of construct unidimensionality was fulfilled for all the six constructs as explained and indicated in Tables 5.8, 5.9, 5.11, 5.12, 5.13 and 5.14. Modification indices and standardised residual were also examined to see whether there was any misspecification in the model (Byrne, 2010). Standardised residual values below 2.50 (Hair et al., 2006) or less than 2.58 (Joreskog, 1993) for all the six constructs indicated no cross loadings among the variables in the measurement models. Standardised residuals are usually used as a diagnostic measure of model fit and computed by dividing residuals by the standardised errors of the residuals. An examination of the standardised regression weights (factor loadings) showed that all the items loaded significantly into their intended factor.

5.3.6 An Analysis of the Structural Model

5.3.6.1 Specifying the Structural Model.

In specifying the structural model, it was determined that the appropriate unit of analysis for this research is the individuals. Subsequently, the proposed model was specified using a path diagram to indicate their relationships. As the research was aimed at examining the engagement of talents to their jobs (JE) or organizations (OE), both these constructs were the fixed parameters whereby the relationships between them were set at 0, and therefore, will not be estimated by SEM. Hence, no arrow was shown here and the theory assumed that the path was equal to 0. The rest of the constructs with arrows between them were free parameters whereby the relationships will be estimated by SEM.

Figure 5.7 shows the combination of the fitted measurement models into a full hypothesised structural model. The hypothesised model of factorial structure for the research framework defines the relationships among the unobserved variables. This model hypothesises a priori that (i) responses to the research framework can be explained by the six factors of PE, JE, OE, JS, ITS and D; (ii) each item had a non-zero loading on the factor that it was designed to measure, and that there were zero loadings on all other factors; and (iii) the error or uniqueness terms associated with the item measurements were uncorrelated. PE or PsyEmp as indicated in the structural diagram was the only exogenous construct while JE (JobEng), OE (OrgEng), JS (JobSat) together with the outcomes, namely ITS (IntenStay) and D (Dedication) were the endogenous constructs. These five constructs (variables) were each interrelated with the constructs included in the model, and each was seen as either a mediator or an outcome based on the hypotheses in Table 3.1. JE and OE had the dual role as the mediator for PE and as an antecedent for JS. JS also served as a possible mediator for JE and OE. In summary, JE, OE and JS were hypothesised as mediators between PE and the talent outcomes namely, ITS and D. The structural theory for the research framework was created by constraining the covariance matrix using the set of free and fixed parameters representing the hypothesised relationships.

In this research, the hypotheses proposed that the construct PsyEmp (PE) was statistically significant and positively related to two constructs; namely, JobEng (JE) and OrgEng (OE). This proposition implied a single structural relationship with JE and OE as functions of PE that were indicated by hypotheses H1 (a) and H1 (b). JobSat (JS) was viewed as a function of JE and OE as indicated by the hypotheses H2 (a) and H2 (b). Subsequently, IntenStay (ITS) and Dedication (D) were outcomes of JS and they were shown as hypotheses H3 (a) and H3 (b). The PE construct was not hypothesised as directly related to ITS and D. As such, the proposed theory involved only one exogenous construct and five endogenous constructs.

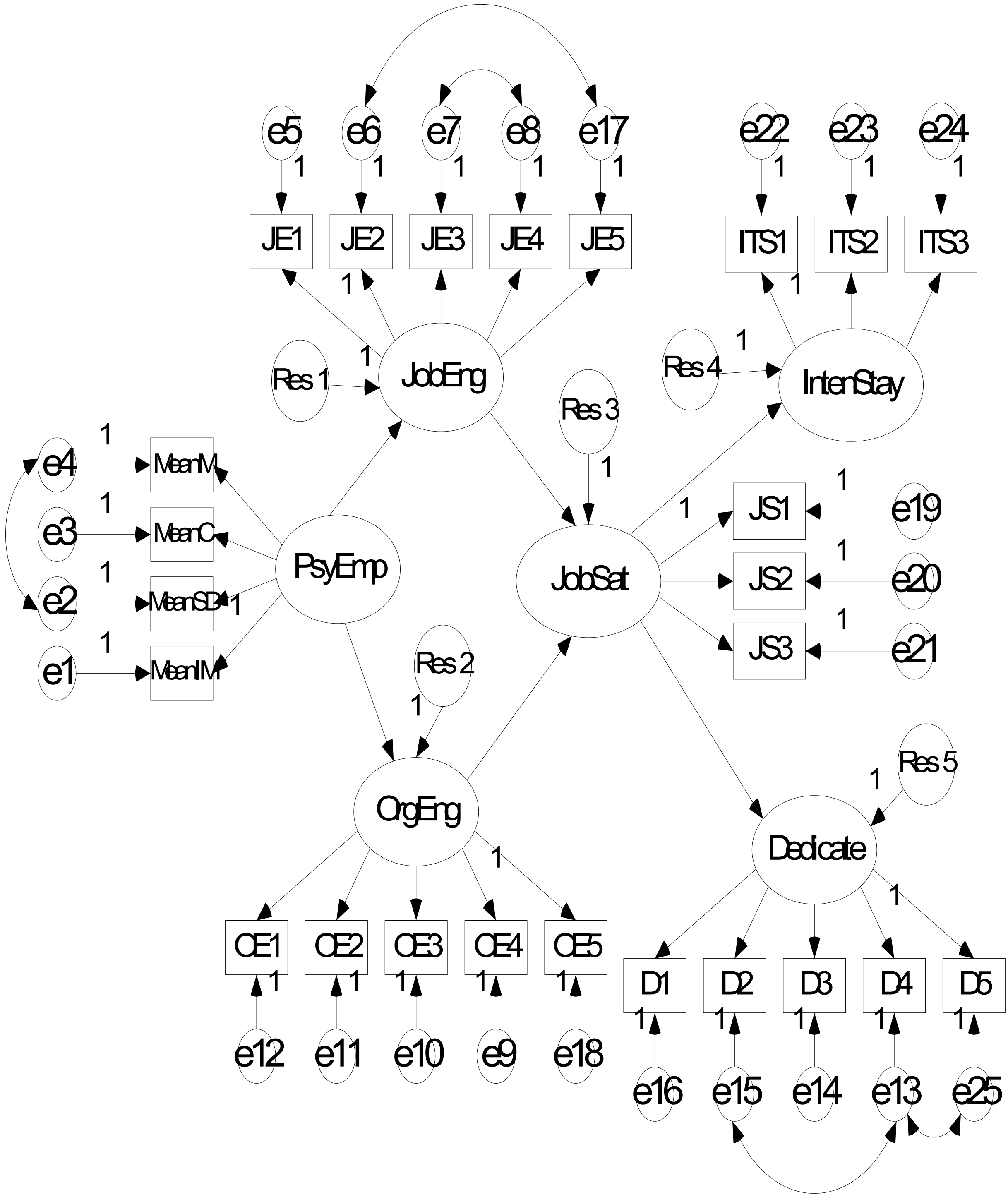


Figure 5.7 **The Combination of Fitted Measurement Models into a Full Hypothesised Model** (initial format with default settings).

Note. PsyEmp = psychological empowerment, JobEng = job engagement, OrgEng = organization engagement, IntenStay = intention to stay, Dedicate = dedication.

The PE construct was exogenous because there were no arrows pointing at it. JE and OE were functions of PE and they are therefore endogenous with arrows pointing at them. ITS and D were functions of JS making them endogenous also. There was no covariance coefficient (represented by a two-headed arrow) among the constructs in the model as covariance matrix includes only relationships between exogenous constructs (Hair et al., 2006). Therefore, any path between the constructs that has no theoretical relationship is set to 0. Five residuals were included in the full structural model to represent the error in predicting the dependent (endogenous) variables from the independent variables. These residuals of Res1, Res2, Res3, Res4 and Res5 reflected the unexplained variance in the latent endogenous variables due to all unmeasured causes.

In the hypothesised structural model, there were 350 distinct sample moments (comprising of sample variances and sample covariances), 86 distinct parameters (comprising of regression weights, covariances, variances and intercepts) that need to be estimated resulting in a degree of freedom (the difference between sample moments and parameters) of 264. This meant that the model was over-identified. According to Ullman (1996), models need to be over identified in order to be estimated and to test hypotheses about relationships among variables. Identification is important as it highlights if there is a unique set of parameters that are consistent with the data. If a model cannot be identified, the model cannot be evaluated empirically (Byrne, 2010). In AMOS, the level of identification of the model depends on the degree of freedom. Therefore, the structural model will be tested by a χ^2 value with 264 degrees of freedom.

The structural model was recursive as the paths between constructs all proceeded in one direction only from the predictor (antecedent) construct of PE to the dependent or outcome constructs (consequences) of ITS and D (Arbuckle, 2009). When testing the structural theory, the CFA factor pattern was used to model the construct loadings. This means that the coefficients for factor loadings and the error variance terms were allowed to be estimated along with the structural model coefficient. According to Hair et al. (2006), besides simplifying the transition from the CFA to the structural testing stage, the CFA factor pattern could reveal any interpretational confounding by comparing the CFA loading estimates with those of the structural model.

Interpretational confounding occurs when the measurement estimates for one construct are being significantly affected by the relationships that are other than those from the specific measures (Hair et al., 2006). However, the authors attest that small fluctuations of 0.5 or less are expected. Analysis of the model input produced the result that the minimum was achieved in the summary model statistics. This implied that AMOS was successful in estimating all the parameters in the model, resulting in a convergent solution. It also meant that the programme was able to reach the minimum discrepancy value defined by AMOS in its comparison of the sample covariance and restricted covariance matrices (Byrne, 2010).

5.3.6.2 The Structural Model Validity.

Through the assessment of the validity and fitness of the six measurement models earlier on pages 107 to 125, it was found that the proposed measurement models have sufficient validities to satisfy the criteria for factor structure validation. In assessing the structural or hypothesised model, the primary focus is on the relationships between the latent constructs (Byrne, 2010). This is based on the structural theory that there must be conceptual representation of the relationships between constructs. Hair et al. (2006) explained that the structural model applies the structural theory by specifying which constructs are related to each other and the nature of each relationship. The nature of relationships between constructs that specifies the structural model will then be used to test the theoretical model of the hypotheses.

The structural equation modelling (SEM) was used to test the structural model by using maximum likelihood analysis. The maximum likelihood analysis is a SEM estimation procedure that produces parameter estimates that mathematically minimise the difference in the covariance matrices for a specified model (Hair et al., 2006). SEM examines the theoretical model empirically by involving both the measurement model and the structural model in one analysis (Hair et al., 2006). Theory is then tested by examining the effect of exogenous construct (predictor) on endogenous constructs (outcomes).

The goodness of the overall fit of the model was assessed to determine how significantly different are the observed covariance structure and the covariance structure implied by the research model. The model fit compares the theory to reality as represented by the data (Byrne, 2010). Accordingly, the closer the values of the estimated covariance matrix and the actual observed covariance matrix, the better fit it is. Among the model fit indexes that were used to assess the fitness of the data and the proposed model are: the chi-square statistics (χ^2) to test the absolute fit of the model, the Goodness-of-Fit Index (GFI), the Adjusted Goodness-of-Fit Index (AGFI), the Comparative Fit Index (CFI), the Normed Fit Index (NFI), and the Root Mean Square Error of Approximation (RMSEA). These fit indices that cover the range of absolute fit measures, incremental fit measures and parsimonious fit measures, are used to establish the acceptability of the SEM model as good practice dictates that more than one fit statistics be used (Byrne, 2010). The acceptable fit between the hypothesised model and the sample covariance matrix would suggest the plausibility of the hypothesised relationships. In any case, there could be moderate level of fitness if the data meets some of the fitness test.

5.3.6.3 The Goodness-of-Fit (GOF) Indices.

The chi-square (χ^2) test is an absolute test of model fit. Together with the ratio of χ^2/DF, a parsimonious fit measure, they are also the test of model discrepancy. It is the fundamental measure used in SEM to quantify the differences between the observed and estimated covariance matrices. The chi-square and χ^2/DF values would reveal to the researcher the extent to which the data (sample covariances) is incompatible with the hypothesis (implied covariances). Data with a better fit with the model gives small χ^2 values and χ^2/DF ratios with values 2 or less (Hair et al., 2006). The χ^2 value increases when the model fitness decreases. The non-perfect fitness is also reflected by smaller probability value for χ^2 test indicating statistical significance. If the ρ-value associated with the χ^2 value is below .05, the model is rejected in absolute fit sense.

Conversely, Hair et al. attest that a structural model demonstrating an insignificant χ^2 value where ρ is greater than .05 or .01 is suggestive of adequate structural fit and that the model fits the sample data. The authors explained that non-significance value means that there is no considerable difference between the actual and the predicted matrices. The noted guideline for χ^2 GOF is that, for any theory to be supported by this test, a small χ^2 value and corresponding large ρ-value should be arrived at to indicate no statistical significant difference between the matrices (Hair et al., 2006).

However, χ^2 is highly sensitive to sample size especially when the observations are greater than 200 (Joreskog, 1993). As sample size increases, so does the χ^2 value even though the differences between matrices are identical. Joreskog (1993) advocates that an alternative evaluation of the χ^2statistic is to examine the model's ratio of the χ^2 value to the degree of freedom. As noted earlier, a small χ^2 value relative to its degree of freedom is indicative of good fit. In order to substantiate this assessment and ascertain overall fit, other descriptive measures of fit such as GFI, AGFI, CFI, NFI and RMSEA are also used since the χ^2 goodness-of-fit criterion is sensitive to sample size and non-normality of data. These selections would cover the groups of GOF measures: absolute fit index (i.e. GFI & AGFI), incremental fit measures (i.e. CFI & NFI), goodness-of-fit index (i.e. TLI), and badness-of-fit index (i.e. RMSEA).

Absolute fit index measures the overall fit of SEM to a set of empirical observations while incremental fit measures contrasts the fit of the maintained model with that of a competing or baseline (null) model (Kelloway, 1995). Besides Byrne (2010), Hoyle

(1995) and Ullman (1996) have also suggested the use of multiple indices when determining model fitness. Additionally, Hair et al. (2006) are of the opinion that a model reporting the χ^2 value and degrees of freedom complemented with the ratio χ^2/DF, the CFI, and the RMSEA would provide sufficient information to evaluate a model.

The GFI or Goodness-of-Fit Index is essentially the ratio of the sum of the squared differences between the observed and implied covariance matrices to the observed variances (Byrne, 2010). It measures the fit between the observed (actual) data (covariance or correlation) matrix and those predicted from the proposed model. The AGFI or Adjusted Goodness of Fit Index is the adjusted version of GFI where the degrees of freedom of a model and the number of unknown variables are taken into consideration for adjustment. Hu and Bentler (1999) highlighted that the values of both GFI and AGFI should fall between zero and one where zero represents no fit and one is perfect fit. Hence, a value above .90 is considered acceptable and a good fit.

RMSEA or Root Mean Square Error Approximation Index incorporates the parsimony criterion and is relatively independent of sample size and number of parameters. Parsimonious fit measures reflect the ratio of estimated parameters to the potential number of degrees of freedom available in the data (Mulaik, James, Van Altine, Bennett, Lind and Stilwell, 1989). RMSEA index measures the discrepancy between the observed and estimated covariance matrices per degree of freedom (Steiger, 1990). Lower RMSEA values indicate better fit. Steiger (1990) recommends that if the value for RMSEA is less than .05, it indicates good fit while values up to

.08 as reasonably fit, and values between .08 and .10 indicate mediocre fit. RMSEA is the badness-of-fit index compared to other indices where higher values produce better fit. A suggested rule of thumb for a RMSEA fit is that a value less than or equal to 0.06 indicates an adequate fit (Hu & Bentler, 1999). However, Hair et al. (2006) argue that the question of what is a *good* RMSEA is debatable. They noted that most acceptable models have values below .10. Mulaik et al. (1989) claim that the RMSEA as a measure of fit has the tendency to ignore the complexity of the model. As such, they recommend that researchers be cautious when applying RMSEA to a complex model.

NFI or Normed Fit Index is a ratio of the difference in the χ^2 value for the fitted model and a null model divided by the χ^2 value for the null model (Hair et al., 2006). Its value ranges between 0 and 1, where 1 indicates a perfect model. By contrast, the CFI or Comparative Fit Index is an improved version of NFI that also has values that range between 0 and 1, with .90 or greater representing an acceptable fit. It compares data against the null model. The CFI was developed by Bentler (1990) as a non-centrality parameter-based index to overcome the limitation of sample size effects.

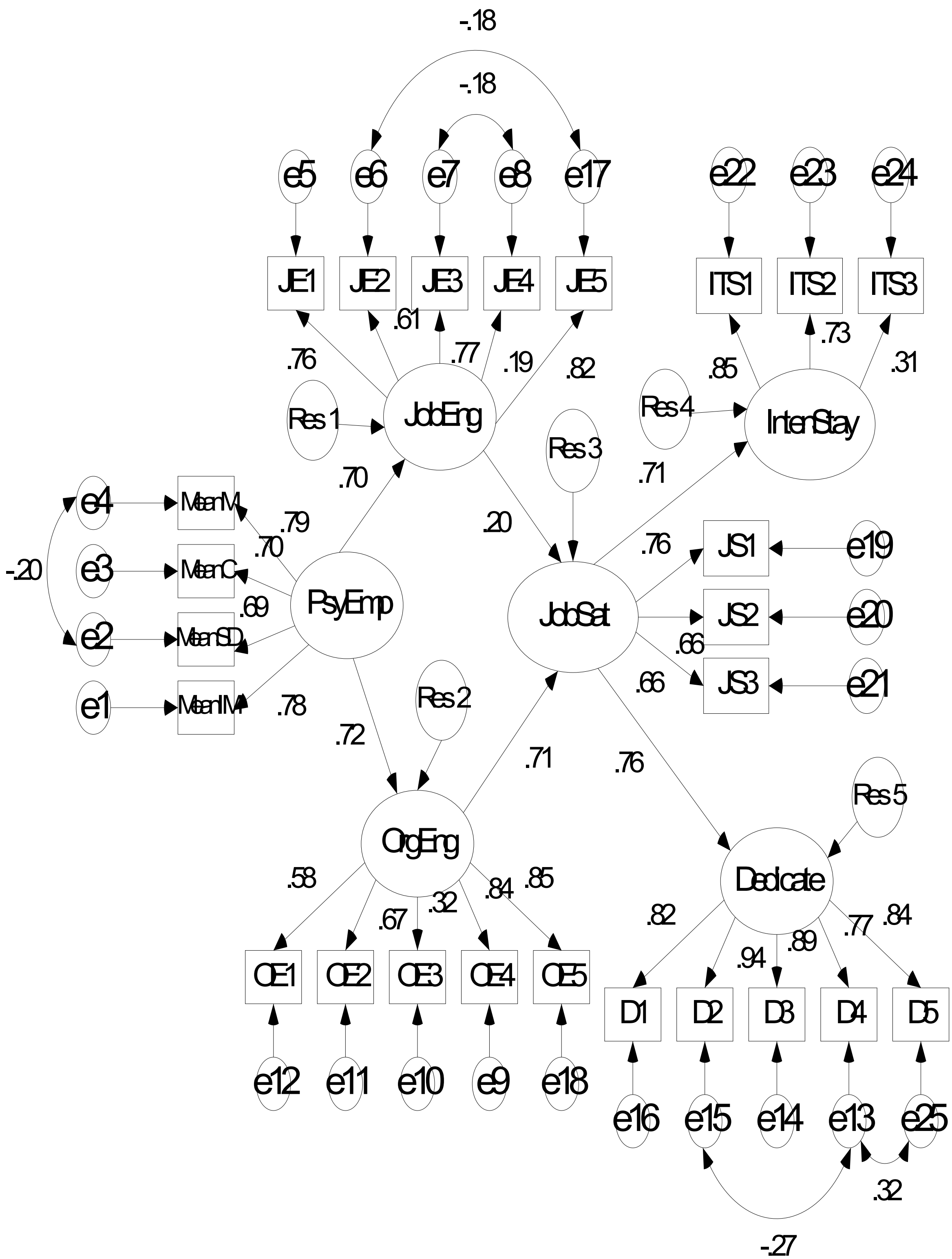


Figure 5.8 **The Computed Hypothesised Model (Standardised Estimates).**

Note. PsyEmp = psychological empowerment, JobEng = job engagement, OrgEng = organization engagement, IntenStay = intention to stay, Dedicate = dedication.

5.3.6.4 Preliminary Assessment of the Hypothesised Model.

Upon computing the combination of the fitted measurement models into a full structural model as shown in Figure 5.7, the AMOS graphical outcome is as displayed in Figure 5.8. In using the CFA factor pattern that allows the coefficients for loadings and error variance terms to be estimated along with the structural model coefficients, small fluctuations were noted as expected (Hair et al., 2006). Except for MeanSD where the factor loading changed from .78 to .69 and job engagement (JE2) where the factor loading changed from .69 to.61 in the full structural model, there was no other standardised loading estimates that vary substantially. The full standardised loading estimate for the hypothesised structural model is presented in Appendix C. Perhaps, the interpretational confounding situation may have existed for both MeanSD and JE2 where their measurement estimates were being significantly affected by relationships other than those among the specific measures. The issue of interpretational confounding highlights the importance of developing and using unidimensional measures.

Unidimensionality is referred to as the existence of one construct underlying a set of items. According to Anderson and Gerbing (1988), achieving unidimensional measurement is a critical aspect of testing SEM as well as a necessary condition for assigning meaning to estimated constructs. In an effort to minimise the potential for interpretational confounding, the two-step approach of Anderson and Gerbing (1988) was used. This two-step approach requires the estimation of a measurement model containing all of the latent constructs and respective indicators before the estimation of the structural model. In addition, the squared multiple correlation or variance extracted value for each of the five endogenous constructs of organization engagement, job engagement, job satisfaction, intention to stay and dedication have met the 50 percent rule of thumb for adequate convergence as recommended by Hair et al. (2006). Details for the full value extracted values of the structural model are displayed in Appendix D. Evidence from the computed structural model indicated that the parameter estimates for the key variables were statistically significant and in the predicted direction. The strength of the causal paths as indicated by the standardised path coefficient was greater than zero for a positive relationship. Hence, the structural model is technically valid.

In addition, this study that used scales with a priori assumptions about construct validity also confirmed the validity of the measures in the model through CFA. This confirmation ascertained that the specific hypothesised measurement structure provided adequate explanation of the covariance between the observed variables (Kelloway, 1995). In the context of convergent validity, the critical ratios (C.R) for the factor loadings were assessed. Critical ratio indicates the statistical significance of parameter estimates. In reviewing the unstandardised estimates as in Table 5.15, the listed parameters were statistically significant given that the C.R. values are $> \pm 1.96$ (Byrne, 2010).

Anderson and Gerbing (1988) advocate that when all the indicators have significant loadings, convergent validity is achieved. This result would in turn support the view that the indicators are effectively measuring each intended construct. The significance of the parameters is also indicative of a sample size that is adequate (Byrne, 2010). Table 5.15 also shows the appropriateness of standard error (S.E.) that reflects the precision with which parameters have been estimated for the variables. Byrne (2010) specified that small S.E. values suggest accurate estimation.

Discriminant validity was also assessed to verify that the scales developed to measure different constructs are indeed measuring different constructs (Garver & Mentzer, 1999). Bagozzi and Philips (1982) advocate that discriminant validity between constructs is achieved when the chi-square value for the unconstrained model is significantly lower than the constraint models. In this research, the six factor model or the full structural model produced the lowest chi-square value and as such, the best model (see Appendix E).

Table 5.15

Standard Error and Critical Ratio of Constructs (Initial Full Model)

	Standard Error (S.E.)	Critical Ratio (C.R.)
JobEng < --- PsyEmp	.051	10.462
OrgEng < --- PsyEmp	.050	11.484
JobSat < --- JobEng	.051	3.623
JobSat < --- OrgEng	.057	10.473
Dedicate < --- JobSat	.108	11.380
IntenStay < --- JobSat	.104	10.835

Note .Three decimal points are presented to show the actual value generated.

5.3.6.5 The Overall Model Fit.

Next, the hypothesis of the model fit was analysed. The hypothesis for testing the model fit is as follows:

H_0: There is no model fit between the observed data and the hypothesised model.
H_1: There is model fit between the observed data and the hypothesised model

The initial fit statistics computed for assessing the structural (hypothesised) model fit are as shown in Table 5.16 below.

Table 5.16

The Initial Fit Statistics for the Structural Model

Model	χ^2	DF	ρ	χ^2 /DF	NFI	CFI	RMSEA
Sample[a]	659.152	264	.000	2.497	.866	.915	.066
Remark	Rather large	_	significant paths	>2 lacks fit	< .90 lacks fit	Meets requirement	< .10 acceptable value

[a] The values are presented in three decimal points to show the actual value generated.

At this stage of the analyses, the structural model fit was compatible to the measurement model fit because the covariance / variance matrix estimated by the model did adequately reproduce the sample covariance or variance matrix. . However, the diagnostic measures in AMOS indicated potential respecification (modification) for the model. The large χ^2 or cmin (minimum discrepancy) value at 659.152, the high χ^2 /DF ratio of 2.497, and the moderate NFI value of .87 suggested the need to improve the model.

A review of the modification indices revealed evidence of misfit in the model. Some modifications in specification were needed to identify a model that would better present the sample data (Byrne, 2010). Although the values of CFI at .92 and

RMSEA at .07 were acceptable, there were still possibilities to improve the fitness of the model with better values of χ^2 /DF and NFI. In this initial hypothesised model, RMSEA had the 90 percent confidence interval ranging from .06 to .07. Additionally, in analysing the PCLOSE value of RMSEA, the hypothesis of *close fit* (i.e. RMSEA is no greater than .05 in the population) the probability of getting the RMSEA value as small as .07 is 0.000 as shown in Table 5.17. However, with a CFI of .92, this meant that the hypothesised model represented a moderate fit to the data. Hence, the alternate hypothesis or H_1 was partially accepted at this stage.

Table 5.17

RMSEA Results of the Initial Hypothesised Model

RMSEA (Initial hypothesised model)				
Model	**RMSEA**	**LO90**	**HI90**	**PCLOSE**
Default model	.066	.060	.073	.000
Independence model	.213	.208	.219	.000

Note. The values are presented in three decimal points to show the actual figures produced.

Generally, the sensitivity of the Likelihood Ratio Test to sample size and its basis on the central χ^2 distribution necessitated a model evaluation beyond χ^2 value for realistic SEM empirical research (Bryne, 2010). Jöreskog (1993) noted that findings of a large χ^2 relative to degrees of freedom commonly indicated a need to modify the model to better fit the data. In assessing the listed statistical recommended modification indices from the theoretical as well as empirical aspects, there was a good rationale and justification that model respecification was worth considering. Any large modification indices would argue for either the presence of factor cross-loadings or error covariances, or both (Bryne, 2010). A modification index refers to the value that represents the expected drop in overall χ^2 value when a parameter was to be freely estimated in the subsequent computation. This rationale is supported by the recommendation of Jöreskog (1993) that, irrespective of whether a respecification is theory or data driven, the ultimate objective is to find a model that is both substantially meaningful and statistically well fitting (Bryne, 2010). Both Jöreskog and Byrne suggest that model respecification is commonly conducted in SEM to improve model fit.

As the estimation of modification indices in AMOS is based on a univariate approach, it is critical that only one parameter is added at a time to the model. This is because the modification indices can change substantially from one tested parameter to another (Byrne, 2010). Therefore, in building the hypothesised Model II, it is most reasonable to add to the model the error covariance having the largest modification index that in this case was the error term e20 <-> e22 for items JS2 and ITS1 with a modification index of 33.336. Although there were other large modification index, this one stands out as it presents misspecified error covariance that maybe be due to content overlap.

The model respecification using correlated errors was justified by substantive rationale. Moreover, forcing large error terms to be uncorrelated is rarely appropriate with real data (Bentler & Chou, 1987). When these variables were allowed to correlate, the chi-square value was reduced subtantially creating a better model. This process of embarking the post hoc model fitting to identify areas of misfit in the model by examining the modification indices meant that the analyses mode could change from confirmatory to exploratory (Byrne, 2010). In the post hoc model fitting, a low probability value ($\rho < .01$) was used to adjust for the increased chances of making a Type 1 error when adjusting a model (Ullman, 1996).

The GOF results for Model II are as shown in Table 5.18. The GOF statistics of Model II with the incorporation of the error covariances of items JS2 and ITS1 improved the model fit. The estimation of Model II yielded an overall $\chi^2_{(263)}$ value of 623.45, a CFI of .92 and a RMSEA of .06. Although the improvement in model fit for Model II compared to the original hypothesised model appeared to be small based on the CFI and RMSEA results, the model difference was statistically significant ($\Delta\chi^2_{(1)}$ = 35.698).

Table 5.18

The GOF Results[a] for Model II

Model	χ^2	**DF**	ρ	χ^2 **/DF**	**NFI**	**CFI**	**RMSEA**
Sample	623.454	263	.000	2.371	.873	.922	.064
Remark (difference)	Much smaller value	1	significant paths	still lacks fit	improved model fit	indicates good model fit	< .06 improved model fit

Note. M.I. = modification index
[a] The values are presented in three decimal points to show the gradual improvement of GOF values for the model after each modication index.

In reviewing the modification indices for Model II, respecification was still needed to determine a well-fitting talent engagement model. The results that are shown for Model II required further modification through the largest qualifying modification index (M.I), i.e. the M.I. for e4 <-> Res3 at 34.911. This modification index is associated with a path flowing from Meaning of PE to Job Satisfaction (JS) with the expected value estimated to be 0.088. Similar to the error covariance between items JS2 and ITS 1, the error covariance between e4 and Res3 could also be redundant due to content overlap. However, this path made good sense as employees who found high meaning in their jobs are likely to exhibit high levels of job satisfaction. Based on this outcome, the path associated with the largest M.I. was focused and the causal structure respecified into Model III. The GOF statistics for this modified model (Model III) revealed a statistically significant improvement in the model fit between Model III and Model II as shown in Table 5.19.

Table 5.19

The GOF Statistics[a] for Model III

Model	χ^2	**DF**	**ρ**	χ^2 **/DF**	**NFI**	**CFI**	**RMSEA**
Sample	585.299	262	.000	2.234	.881	.930	.06
Remark (difference)	decreased by 38.155	1	significant paths	-0.137	still lacks good fit	- minimal improvement -	

Note. M.I= modification index
[a] The values are presented in three decimal points to show the gradual improvement of GOF values for the model after each modication index.

Model III yielded an overall $\chi^2_{(262)}$ value of 585.299 with CFI = .93 and RMSEA = .06. The χ^2 difference between Model II and Model III was statistically significant at $\Delta\ \chi^2_{(1)}$ = 38.155. In reviewing the modification indices for Model III, the largest modification index of 23.103 was associated with the path between competency and self-determination (e2<->e3). Bearing in mind on the importance of substantial meaningfulness of inclusion, it was reasonable that employees who exhibit high competence also exhibit high levels of self-determination. As such, this path was reestimated again into Model IV.

Table 5.20 showed that Model IV yielded a χ^2 value of 556.169 with 261 degrees of freedom, χ^2 /DF of 2.131, CFI of .936 and RMSEA of .058. The difference in fit between Model IV and Model III was also statistically significant at $\Delta\ \chi^2_{(1)} = 29.13$. As the RMSEA and χ^2 /DF can still be improved further, the next modification index to consider was the covariance of e8<->e10 with the largest expected par change of 0.206. Kaplan (1989) suggests the appropriateness of basing respecification on size of the parameter change statistics instead on modification indices. As this was substantively meaningful, his suggestion was accepted to estimate Model V.

Table 5.20

The Modification Results for Model Fitness

Model	M.I.	χ^2	DF	ρ	χ^2 /DF	NFI	CFI	RMSEA	ECVI
IV	e2 <-> e3 3rd M.I. of 23.103	556.169 (Δ = 29.13)	261	.00	2.131	.887	.936	.058	2.166
V	e8 <-> e10 4th M.I. of 20.759	534.646 (Δ =21.523)	260	.00	2.056	.891	.941	.056	2.108
VI	Res5 <-> Res2 5th M.I. of 24.610	491.783 (Δ = 42.863)	259	.00	1.899	.900	.950	.051 LO90 = .045 HI90 = .058 PCLOSE = .354	1.988
VII	e6 <-> e7 6th M.I. of 13.317	467.73 (Δ = 24.053)	258	.00	1.821	.905	.954	.049 LO90 = .042 HI90 = .056 PCLOSE = .565	1.928
VIII	e5 <-> e6 7th M.I. of 15.872	441.582 (Δ = 26.148)	257	.00	1.718	.910	.96	.046 LO90 = .039 HI90 = .053 PCLOSE = .813	1.851

Note. M.I.= modification index
The values are presented in three decimal points to show the gradual improvement of GOF values for the model after each modication index.

The estimation of Model V as shown in Table 5.20 yielded a $\chi^2_{(260)}$ value of 534.646, χ^2 /DF of 2.056, CFI of .941 and RMSEA of .056. The difference in fit between Model V and Model IV was statistically significant at $\Delta \chi^2_{(1)} = 21.523$. The estimated parameter value that exceeded the parameter change statistics estimated value was also statistically significant with the critical ratio of 4.441. From a substantively meaningful perspective, high level of organization engagement would generate high dedication. Since the cmin value of 2.056 still exceeded the threshold of 2.0 (Hair et al. 2006), the largest modification index for Model V, the covariance of Res5<->Res2, was used for subsequent modification into Model VI.

Model VI yielded a χ^2 value of 491.783 with 259 degrees of freedom, χ^2 /DF of 1.899, CFI of .950, and RMSEA of .051. Again, the difference in fit between Model VI and Model V was statistically significant at $\Delta \chi^2_{(1)} = 42.863$. However, the strength of the PCLOSE value for RMSEA was rather low at .354 and the value for RMSEA could still be improved. The next modification index that was considered was the covariance of e6<->e7 with the largest expected par change of 0.083. As this covariance was substantively meaningful, the model was respecified into Model VII.

Table 5.20 showed that the estimation of Model VII yielded a $\chi^2_{(258)}$ value of 467.73, χ^2 /DF of 1.821, CFI of .954, and RMSEA of .049. The difference in fit between Model VII and Model VI was again statistically significant at $\Delta \chi^2_{(1)} = 24.053$. Even the estimated covariance (.141, C.R. = 4.585) was larger than the estimated par change of 0.083. The results from this analysis showed that Model VII was the best fit to the data. Before confirming this model, the issue of model parsimony was analysed to ensure that all the hypothesised paths were relevant to the model. This was necessary because of their statistically significant C.R. value of ±1.96 and above. Results from Model VII indicated that all the hypothesised paths were statistically significant. In the interest of securing a better fit model, the final largest modification index of e5 <-> e6 with the largest par change of 0.094 in Model VII was modified into Model VIII.

In the final model as shown in Table 5.20, Model VIII, the estimation yielded a $\chi^2_{(257)}$ value of 441.582 with χ^2 /DF of 1.718, CFI of .96, and RMSEA of .046. Again, the difference in fit, $\Delta \chi^2_{(1)} = 26.148$ was statistically significant. Results for RMSEA at .046 were also much better with the intervals of LO90 at .039 and HI90 at .053, supported by the high value of PCLOSE at .813. Based on these results, the modification process was repeated after analysing the resulting modification indices and par change until the GOF indices for the hypothesised model showed a statistical significant drop in the chi-square value with evident improvements in χ^2 /DF, NFI, CFI and RMSEA. Cognisance was taken on the importance of modifying the model to include only those parameters that are substantively meaningful and relevant. An important finding as the modification process advanced was the drop in the number of modification indices resulting from each subsequent model. This finding emphasises the importance of incorporating additional parameter one at a time into the model. Results of the modification process undertaken towards model fitness are as shown in Table 5.20.

The best fitted model was found after seven (7) modification processes as shown in Table 5.20 and Figure 5.9. The GOF related to Model VIII revealed a statistically significant drop in the chi-square value from Model VII with $\chi^2_{(257)} = 441.582$ and $\Delta \chi^2_{(1)} = 26.148$. There was also improvement in χ^2 /DF ratio that dropped from 1.821 to 1.718; the NFI and CFI were more than .90; and RMSEA (.046 versus .049) with a much better PCLOSE value at .813. With respect to the modification indices of Model VIII, there was no evidence of a substantially reasonable misspecification in the model. Figure 5.9 shows the best-fitting and the most parsimonious Model VIII in representing the data.

As there would be a comparison of a series of models in the quest of obtaining a final well-fitting model, the ECVI or Expected Cross-Validation Index is of interest (Byrne, 2010). In a single sample, the ECVI assesses the likelihood that the model cross-validates across similar-sized samples from the same population (Browne & Cudeck, 1989). Apart from being used with a relative framework whereby a lower ECVI is favoured, it has no other substantive meaning. Table 5.21 compared the ECVI values and confidence intervals of the last three models (Models VI, VII & VIII). It showed that Model VIII (the final fitted hypothesised model) had intervals that range between 1.691 and 2.035. Since the lower value of ECVI is favoured, results in Table 5.21 indicated that Model VIII was the best fitting model for the data and represented a reasonable approximation of the population.

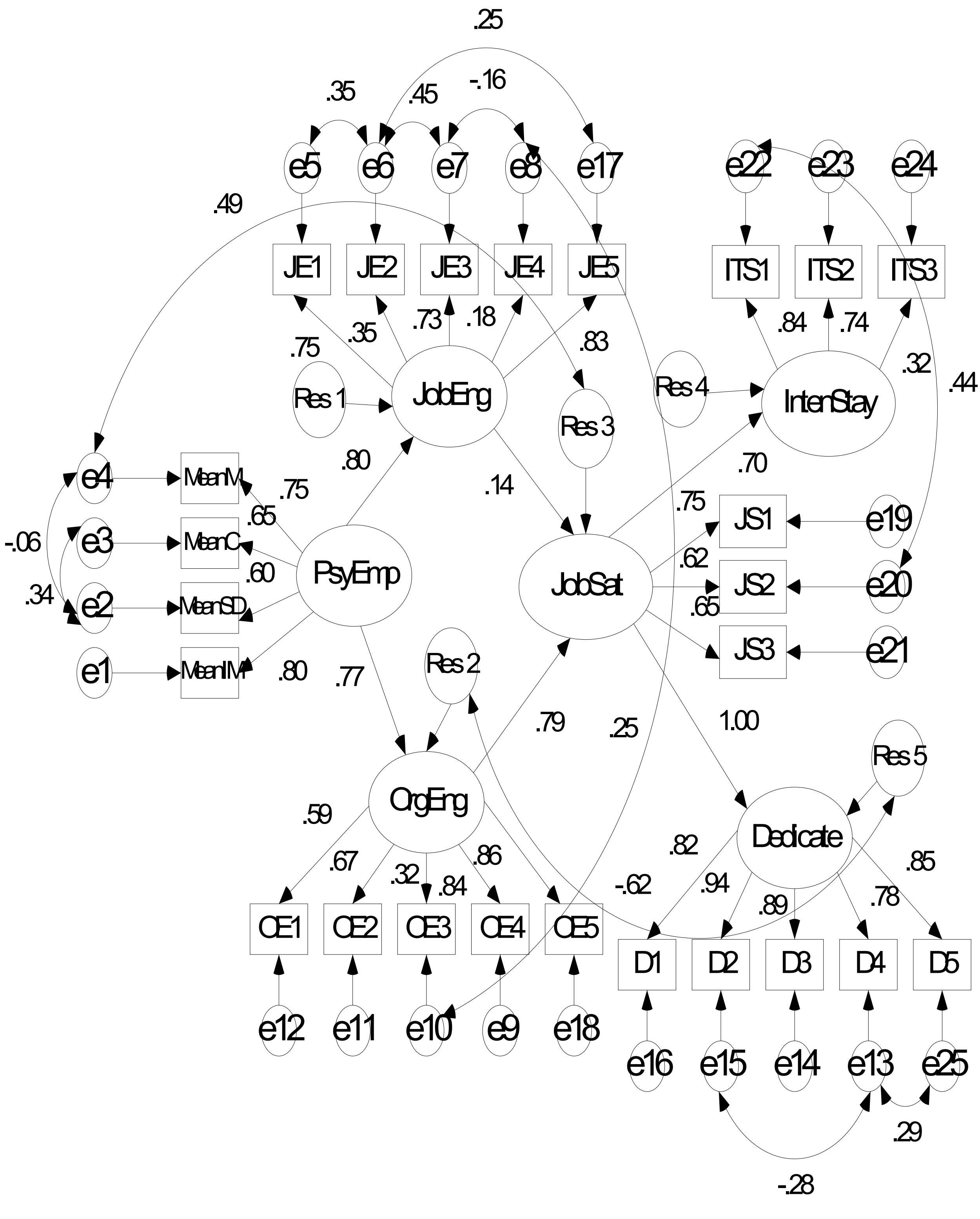


Figure 5.9 **The Full Structural Model that has achieved Model Fit after 7 Modication Processes (Standardised Estimates)**

Note. PsyEmp = psychological empowerment, JobEng = job engagement, OrgEng = organization engagement, IntenStay = intention to stay, Dedicate = dedication.

Table 5.21

ECVI of Model VI, Model VII and Model VIII

	ECVI	LO90	HI90	MECVI
Model VIII (with 7 M.I)	1.851	1.691	2.035	1.897
Model VII (with 6 M.I)	1.928	1.761	2.119	1.973
Model VI (with 5 M.I)	1.988	1.814	2.184	2.032

Note. The values are presented in three decimal points to show the gradual improvement of GOF values for the model. M.I = modification indices; ECVI = expected cross-validation index; LO90 = lowest 90 % confidence interval; HI90 = highest 90% confidence interval; MECVI = modified ECVI.

The pattern of variances and covariances in the data were therefore more consistent with the specified structural (path) model. Ullman (1996) highlights that, when the ratio between χ^2 and DF is less than two, the model has a good fit. Browne and Cudeck (1993) advocated that values of RMSEA less than .05 indicate good fit while values as high as .08 represent errors of approximation in the data. The criteria of constructs unidimensionality was again supported with the results of the well fitting Model VIII with χ^2= 441.582 at ρ< .01; χ^2/DF ratio = 1.718; NFI = .91; CFI = .96 and RMSEA = .05. Even though the χ^2 statistic was significant, other indices (χ^2/DF, NFI, CFI and RMSEA) showed values of above the recommended level for an adequately fitting model.

Table 5.22

RMSEA Results of the Revised Hypothesised Model

RMSEA				
Model	**RMSEA**	**LO90**	**HI90**	**PCLOSE**
Default model	.046	.039	.053	.813
Independence model	.213	.208	.219	.000

Note. The values are presented in three decimal points to reveal the actual values achieved.

The RMSEA value for the modified hypothesised model as noted in Table 5.22 was .046 with the 90% confidence interval ranging from .039 to .053 and the ρ-value for the test of closeness of fit equal to .813. These RMSEA values of .046, .039 and .053 are well within the recommended range of acceptability of < .05 to .08 (Byrne, 2010). Jöreskog (1993) suggests that the ρ-value for RMSEA's closeness of fit test (PCLOSE) should be > .50. Hence, with a PCLOSE value of .813, Model VIII is accepted. Compared to the RMSEA results in Table 5.17 whereby it was only moderately acceptable, its ρ-value of .00 was far from the closeness to fit. The confidence interval of the revised hypothesised model as reported in Table 5.22 revealed a 90% confidence that the true RMSEA in the sample would fall within the LO90 and HI90 interval range of .039 and .053. In addition, since the probability value associated with this test of close fit at ρ = .813 is > .50; the modified hypothesised model therefore fits the data well.

Based on the research findings, the modified model fitted the data; the null hypothesis suggesting that there was no model fit between the observed data and the hypothesised model was not accepted. However, an accepted model is only a not-disconfirmed model. There may be other unexamined models that may fit the data well or better (Byrne, 2010). With the model achieving an acceptable fit, individual estimates of free parameters were subsequently assessed by analysing the standard error (S.E) and the critical ratio (C.R). Table 5.23 shows that all the free parameters met the small value criteria for S.E suggesting accurate estimation of the constructs, and the > ±1.96 value for C.R for the relationship to have statistical significance.

Table 5.23

Standardised Regression Weights, Standard Error and Critical Ratio of Constructs (After model modifications)

	Standard Regression weights	Standard Error (S.E)	Critical Ratio (C.R)
JobEng < --- PsyEmp	.803	.051	11.451
OrgEng < --- PsyEmp	.767	.050	12.274
JobSat < --- JobEng	.144	.051	2.534
JobSat < --- OrgEng	.792	.059	11.061
Dedicate < --- JobSat	.998	.140	11.686
IntenStay < --- JobSat	.699	.104	10.449

Note. The values are presented in three decimal points to show the actual figures produced.

5.3.7 Hypotheses and Mediation Analysis

With the hypothesised model accepted, the next step was to interpret the standardised path coefficients in the model. In AMOS, the standardised structural coefficients are known as standardised weights (Arbuckle, 2009). The findings showed that PE was statistically significant and positively related to JE and OE with standardised coefficients of .80 and .77 respectively; JE and OE were positively related to JS with standardised coefficient of .14 and .79 respectively; and JS was also statistically significant and positively related to ITS and D with standardised coefficient of .70 and .998[1] respectively. Table 5.24 reports the standardised paths of the hypothesised model. The hypotheses H1 (a), H1 (b), H2 (a), H2 (b), H3 (a) and H3 (b)[2] were therefore supported in the full structural model.

[1] The value was presented in three decimal points to show the actual figures produced.
[2] H1(a): PE is positively related to JE; H1(b): PE is positively related toOE
H2(a): JE is positively related to JS; H2(b): OE is positively related to JS
H3(a) JS is positively related to ITS; H3(b): JS is positively related to D.

Table 5.24

Standardised Paths of the Hypothesised Model

Hypothesis	Causal Path	Standardised Path Coefficient
H1 (a)	PE -> JE	.803
H1 (b)	PE -> OE	.767
H2 (a)	JE -> JS	.144
H2 (b)	OE -> JS	.792
H3 (a)	JS -> ITS	.699
H3 (b)	JS -> D	.998

Note. PE = Psychological Empowerment; JE = Job Engagement; OE = Organisation Engagement; JS = Job Satisfaction; ITS = Intention to Stay; and D = Dedication.The values are presented in three decimal points to show the actual figures produced.

The significant and positive relationship of psychological empowerment (PE) with organization engagement (OE) and job engagement (JE) reinforced Saks' (2006) findings that perceived organizational support which is PE, were significantly associated with JE at .36 (ρ <.01) and OE at .26 (ρ <.001) respectively. The positive relationship between job satisfaction (JS) and intention to stay (ITS) reiterated the findings of Mobley (1977) that the relationship between JS and turnover (the reverse of ITS) is significant and consistent. This finding was also supported by the research work of Porter et al. (1974) as well as Porter and Steers (1973). Porter et al. (1974) attest that aspects of work environment (i.e. psychological empowerment) could bring about the association of job satisfaction with affective response such as dedication. Hence, the positive relationship between JS and dedication (D) was supported.

However, Chin (1998) proposes that standardised paths should be at least .20 and ideally above .30 to be considered meaningful. It is noted from Table 5.24 that, although there was positive association between job engagement and job satisfaction (Hypothesis 2a) with a standard path coefficient of .144, this path has failed to meet the minimum benchmark for path strength. This means that the causal path of JE -> JS adds minimal value to the understanding of the relationship between job engagement and job satisfaction. This outcome differentiates organization engagement that displayed significant and positive relationship with job satisfaction.

Mediation refers to the mechanism that accounts for the relationship between the predictor and the criterion. Full mediation is deemed to occur when the relationship between a predictor (exogenous construct) and outcome (endogenous construct) becomes insignificant after a mediator is entered as an additional predictor (Hair et al., 2006). The authors explain that this mediating effect refers to the effect of a third variable (construct) intervening between two other related constructs.

In this study, there were six variables in the recursive model that the effects of mediation were assessed based on the suggestion of Baron and Kenny (1986). It was a recursive model because the paths between the constructs all proceeded from the antecedent construct (PE) to the consequences in one direction with no feedback loops. All the six constructs were found to have significant correlations among them, suggesting possible mediation in the research model.

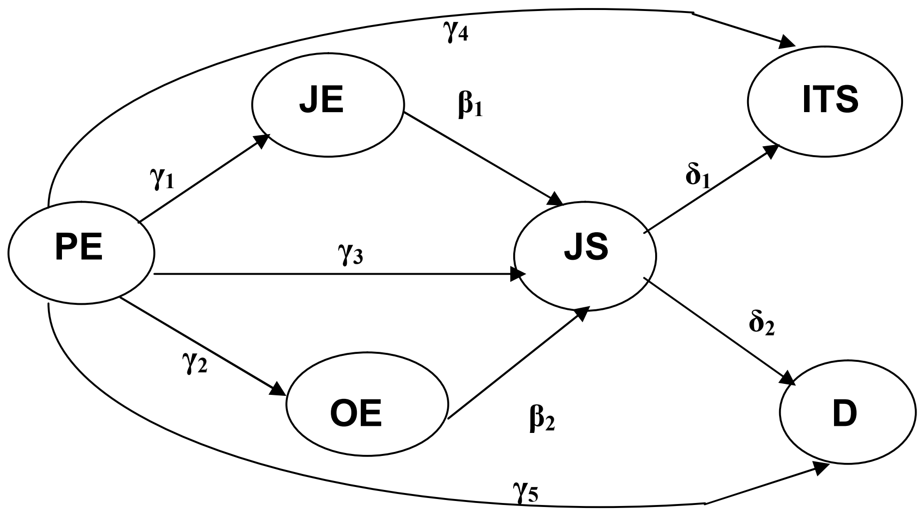


Figure 5.10 **Path Diagram showing Specified Hypothesised Structural Relationships**

Note. PE is the independent variable. JE, OE and JS are the mediating variables. ITS and D are the dependent variables.

PE = Psychological Empowerment; JE = Job Engagement; OE = Organisation Engagement; JS = Job Satisfaction; ITS = Intention to Stay; and D = Dedication

Figure 5.10 shows that JE, OE and JS were mediators when variations in PE significantly account for variations in JE and OE (i.e. path γ_1 and γ_2). Similarly, variations in JE and OE significantly account for variations in JS (i.e. path β_1 and β_2). Besides, variations in JS should also significantly account for variations in ITS and D (i.e. path δ_1 and δ_2) as they are positively correlated. In addition, when paths $\gamma_{1,}$ $\gamma_{2,}$ $\beta_{1,}$ $\beta_{2,}$ δ_1 and δ_2 were controlled, a previously significant relationship between PE and the dependent variables, ITS and D were no longer significant. Therefore, the significant relationship between PE and ITS could be explained by the PE-JE-JS-ITS and PE-OE–JS-ITS relationships.

Similarly, the significant relationship between PE and D can be explained by the PE–JE- JS-D and PE-OE–JS–D relationships. The strongest demonstration of mediation occurred when the paths $\gamma_{3,}$ γ_4 and γ_5 were zeros. When $\gamma_{3,}$ γ_4 and γ_5 were fixed (set at 0), and the model suggested that the sequence of PE-JE or OE – JS-ITS and PE-JE or OE-JS-D provided good fit, thus supporting the mediating roles for JE, OE and JS. However, when paths $\gamma_{3,}$ γ_4 and γ_5 were freed and they improved the model fit significantly as indicated by the change in χ^2, then the mediation role of JE, OE and JS would not be supported. However, if these two models produce similar fits, mediation is still supported (Hair et al., 2006).

Mediation Results

The findings in Table 5.25 suggested the appropriateness of the partially mediated model. The chi-square differences test results indicated a significant of fit for the partially mediated model ($\Delta\ \chi^2 = 31.25$, $\rho < 0.01$). The partially mediated model also indicated a significant improvement on the non-mediated model ($\Delta\ \chi^2 = 89.91$, $\rho < 0.01$). Thus, the findings suggest that the partially mediated model was a slightly better fit to the sample data with $\chi^2 = 410.34$ at $\rho = 0.00$; $\chi^2/DF = 1.62$; CFI = 0.97; TLI = 0.96 and RMSEA = 0.04. These showed that there were direct and indirect relationships between the predictor variable and the dependent variables. These results also indicated that, apart from PE –>JE and PE->OE, there were also direct relationships between PE and JS, between PE and ITS, and between PE and D as shown in Figure 5.11. Figures 5.9 and Figure 5.11 suggest that hypotheses H4 (a) and H4 (b)[3] are partially supported as there were both direct relationships (Figure 5.11) and indirect relationships (Figure 5.9) among PE, JE, OE and JS.

[3] H4(a): JE mediates the relationship between PE and JS; H4(b): OE mediates the relationship between PE and JS.

Table 5.25

Findings from the Mediation Analysis of the Fitted Model

Model	χ^2	**DF**	$\Delta\chi^2$	**NFI**	**TLI**	**CFI**	**RMSEA**	χ^2**/DF**
Model 1[4] (Full mediation)	441.582	257		.910	.953	.960	.046 LO90 = .039, HI90 = .053, PCLOSE = .813	1.718
Model 2 (Partial mediation)	410.337	254		.917	.960	.966	.043 LO90 = .035, HI90 = .050, PCLOSE = .949	1.616
Model 3 (Non-mediation)	500.244	258		.898	.939	.948	.053 LO90 = .046, HI90 = .059, PCLOSE = .259	1.939
Difference (Model 1- Model 2)		3	31.245					
Difference (Model 3 – Model 2)		4	89.907					

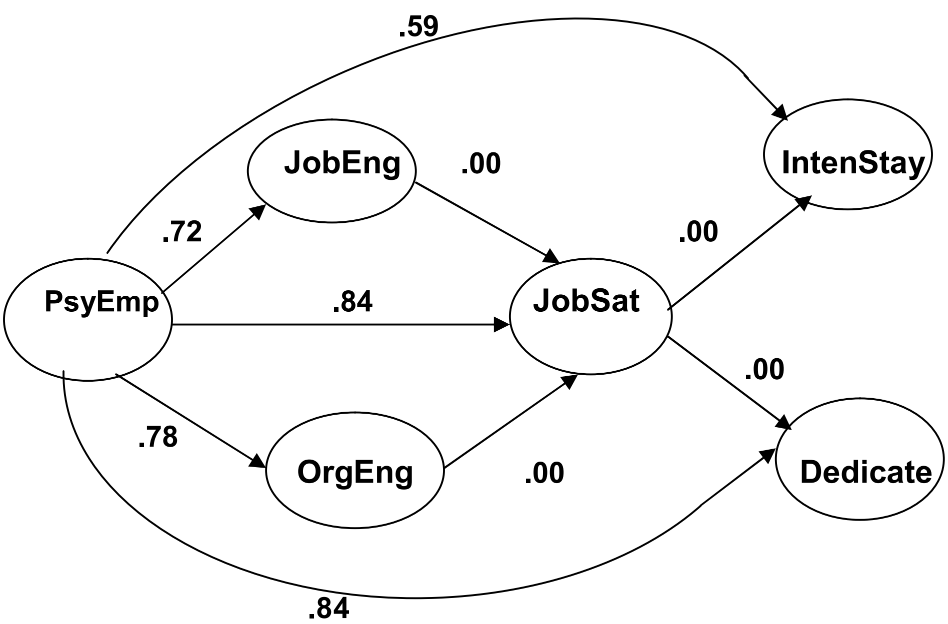


Figure 5.11 **Mediation analyses for Hypotheses 4 & 6.**

(This is a simplified graphic without showing the measuring indicators and errors)

Note. PsyEmp = psychological empowerment, JobEng = job engagement, OrgEng = organization engagement, IntenStay = intention to stay, Dedicate = dedication.

[4] Model 1 = Default model

Figure 5.11 shows that when PE is directly related to JS, ITS and D, the role of JS as the second level mediator becomes redundant (not significant) as indicated by the zero values between JE-JS, OE-JS, JS-ITS and JS-D. The results showed strong positive regression weights of PE with JE, OE, JS, ITS and D at .72, .78, .84, .59 and .84 respectively. These findings were theoretically acceptable as psychological empowerment was shown to be related to job engagement, organization engagement, job satisfaction, intention to stay and dedication (Spreitzer, 1995, 1996 & 1997). Since the partially mediated model provided the better fit, this revealed that job satisfaction did not fully mediate the relationships between psychological empowerment and all the other dependent variables, namely job engagement, organization engagement, intention to stay and dedication. Based on these findings and the zero values indicated in Figure 5.11, hypotheses 6(a), 6 (b), 6 (c) and 6 (d)[5] were not supported**.** Hypotheses 6 had proposed that (a) JS mediates the relationship of PE and JE with ITS; (b) JS mediates the relationship of PE and JE with D; (c) JS mediates the relationship of PE and OE with ITS; and (d) JS mediates the relationship of PE and OE with D.

The full structural model in Figure 5.9 showed that job satisfaction mediates the relationship between JE and ITS, JE and D, OE and ITS, as well as OE and D. However, in Figure 5.12 the analysis showed direct effects also exist between JE and D as well as between OE and D with the path values of .34 and .17 respectively. The relationships of JE->ITS and OE->ITS showed negative values or weak associations

[5] H6(a): JS mediates the relationship of PE & JE with ITS; H6(b): JS mediates the relationship of PE & JE with D; H6(c): JS mediates the relationship of PE & OE with ITS; H6(d): JS mediates the relationship of PE & OE with D.

of -.15 and - .06 respectively. The indirect paths were positively related implying that the paths of JE-> ITS and OE->ITS were better mediated by JS with the resulting effects of .12 and .63 respectively.

JE indicated significant direct effect with dedication at .34 compared to its weak outcome at .05 when mediated by JS. The path of OE->D was mediated by JS with the effect value of .27 compared to the direct effect of .17. These analyses were based on the recommendation of Chin (1998) that standardised paths should be at least .20 and ideally above .30 in order to be considered meaningful. JS partially mediated JE and OE with D as there are positive direct effects of JE -> D and OE -> D. These findings on JS as the mediator between JE and ITS, between JE and D, between OE and ITS, and between OE and D are shown in Figure 5.12 and Table 5.26.

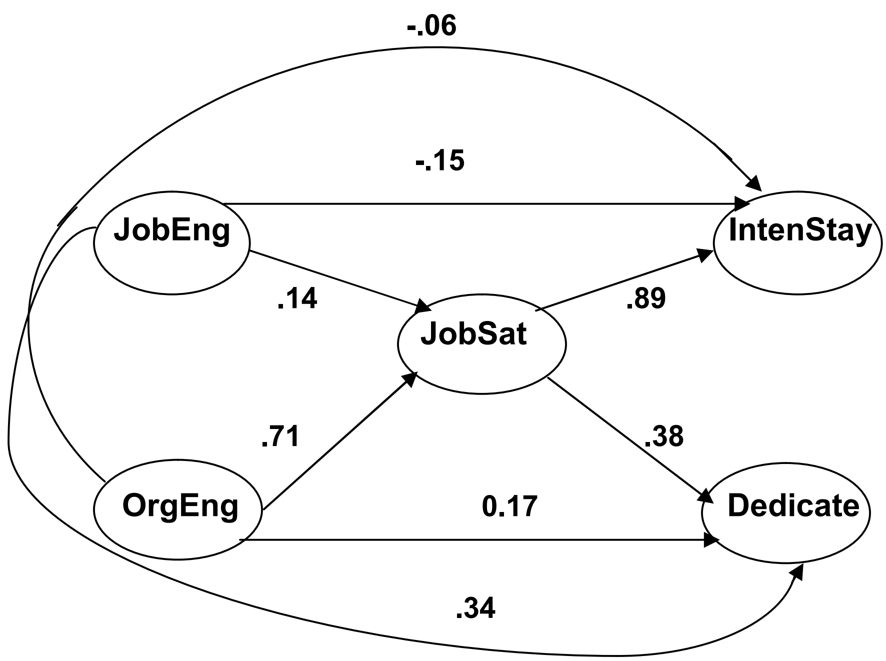


Figure5.12 **Mediation analyses for Hypothesis 5.**

Note. PsyEmp = psychological empowerment, JobEng = job engagement, OrgEng = organization engagement, IntenStay = intention to stay, Dedicate = dedication.

Table 5.26

The Standardised Path Coefficients of JS as the Mediator (see Figure 4.12)

The variables	The standardised path coefficients for direct effects	The total standardised path coefficients for indirect effects
JE -> ITS	-.15	-
JE -> D	.34 √	-
OE -> ITS	-.06	-
OE -> D	.17	-
JE -> JS -> ITS	-	.14 x .89 = .12 √
JE -> JS -> D	-	.14 x .38 = .05
OE -> JS -> ITS	-	.71 x .89 = .63 √
OE -> JS -> D	-	.71 x .38 = .27 √

The findings in Table 5.27 also suggested the appropriateness of the partially mediated model. The chi-square differences test results indicated a significant fit for the partially mediated model ($\Delta\ \chi^2$ = 31.04, ρ < .01). Job satisfaction therefore partially mediates the relationship between JE and OE for a better sample data fit with χ^2 = 410.54 at ρ = .00; χ^2/DF = 1.62, CFI = .97, TLI = .96 and RMSEA = .043. The results revealed that there were also the direct relationships between JE with ITS and D, and OE with ITS and D. Based on the research findings, there were both direct and indirect effects between JE and D as well as between OE and D where JS mediates the relationship of JE and OE with D positively. The negative direct effects of JE and OE with ITS indicated that the relationship of JE and OE with ITS were better supported by the mediation of JS. As such, hypotheses 5(a) and 5(c)[6] were supported while hypothesis 5(b) and 5 (d) were partially supported due to the

[6] H5(a): JS mediates the relationship between JE & ITS; H5(b): JS mediates the relationship between JE & D; H5(c): JS mediates the relationship between OE & ITS; H5(d): JS mediates the relationship between OE & D.

presence of the positively direct effects between JE and D as well as between OE and D.

Table 5.27

Findings showing the Mediation of JS for Hypotheses 5

Model	χ^2	**DF**	$\Delta\chi^2$	**X^2/DF**	**CFI**	**TLI**	**RMSEA**
(1) With full mediation of JS	441.58	257		1.718	.96	.95	.046
(2) With partial mediation of JS	410.54	253		1.623	.97	.96	.043
Difference of (1) - (2)		4	31.04				

Summary of Results

The six constructs, namely psychological empowerment, job engagement, organization engagement, job satisfaction, intention to stay and dedication for the study revealed acceptable internal reliabilities with the Cronbach's alphas that ranged from .64 to .93 (Hair et al., 2006). Correlations among the constructs were statistically significant indicating that there were relationships between the constructs. The KMO measure of sampling adequacy values for the constructs were larger than .5 indicating that the correlations among them can be explained by other variables (Malhotra, 2007). The overall significance of the correlations among the six constructs was noted by the Bartlett's test of sphericity (Hair et al., 2006).

This over-identified research model met the four validity tests of construct, discriminant, face and nomology as advocated by Hair et al. (2006). The findings were complemented by the validity of the six measurement models with acceptable goodness-of-fit results. The structural model that was tested achieved an acceptable level of model fit after seven theoretically and logically supported modification indices. The hypotheses analyses on the computed data indicated a mixture of full and partially supported results. The research findings would be discussed in the next chapter.