Covariance Based and Partial Least Square Structural Equation Modeling to Model Job Satisfaction among Lecturers

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Abstract: The universities in Malaysia indirectly contribute to the nation’s future development by developing a pool of professionally educated and trained employees. Therefore, the main purpose of the study is to investigate the factors influencing on job satisfaction namely workload, work-place environment, and relationship with colleagues, management style, promotional opportunities and remuneration using Covariance-Based Structural Equation Modeling (CB-SEM) and Partial Least Square-Structural Equation Modeling (PLS-SEM). This study used self-administered questionnaires which were distributed to lecturers from Universiti Tun Hussein Onn Malaysia. This study found that workload, relationship with colleagues; management style and remuneration were significantly affect job satisfaction of lecturers using CB-SEM. Meanwhile, the factor of workload, relationship with colleagues, promotional opportunities and remuneration were significantly affect job satisfaction of lecturers using PLS-SEM. Overall, the PLS-SEM was more reliable and valid method for modeling job satisfaction among lecturers since the factor loading and Average Variance Extracted values during Confirmatory Factor Analysis (CFA) were higher than CB-SEM.

Index Terms: covariance, job satisfaction, structural equation modeling.

I. INTRODUCTION

Educational institutes are bearing the highest cost in case of managing the human capital of faculty. Therefore, bringing high quality in program delivery necessitates the research on contributing factors of satisfaction and loyalty. The level of satisfaction, which guarantees a successful educational institute, backed by the number factors like strong interactive process, inherent attraction for quality brains, likeness to stay on job and feelings of empowerment. Locke and Lathan (1990) define job satisfaction as pleasurable or positive emotional state resulting from the appraisal of one’s job or job experience. Job satisfaction is a result of employee’s perception of how well their job provides those things that are viewed as important. Satisfaction also develops high level of institutional commitment and desire to show substantial performance.

The high performance do not only based on job satisfaction, but also requires satisfaction with career in education, which positively influences teaching effectiveness and resultantly, students learning. According to Truell et al. (1998), the faculty satisfaction always attracts the attention of academic scholars and frequently touched by social scientists and educational thinkers. The attitude shift corresponds to a complex placement of behavioral cognitions, emotions, behavioral tendencies and overall working style (Ayan and Kocacik, 2010). The decreased satisfaction and lack of commitment brings inefficiency and looseness in teachers and students (Wu et al., 1996).

Job satisfaction is an attitude emanated from employees’ perceptions of their jobs or work environments and refers to the extent to which a person likes his/her job (Pool, 1997; Spector, 1997). The level of job satisfaction reflects and is affected by one’s work experiences as well as his/her present situation and future expectations.

The characteristics of the academic profession are not frequently met in other professions, such as autonomy, freedom and flexibility as well as the teaching/research conflict, the tenure system which provides job security, etc. (Kelly, 1989). Meyer and Evans (2003), found that their internal motivation and the particular importance they attribute to the characteristics of the academic profession (such as autonomy and flexibility) counterbalance the multiple requirements, the strong pressures, the animadversions and the poor financial rewards. Actually, flexibility and autonomy have been considered as key factors in becoming and remaining an academic (Bellamy et al., 2003).

Chong et al. (2010) had studied the influence of job satisfaction among lecturers in Malaysia and found that management support, salary and promotion opportunities are significantly correlated with job satisfaction with positive relationships. Doghonadze (2012) factors contributing lecturers’ job satisfaction in Turkey and found that workload, facilities provided in university and management styles are factors influencing job satisfaction among lecturers.

Ramanathan and Muyldermons (2011) factors influence on sales of soft drinks in UK and found that promotions, special days, seasonal factors and customers’ preferences for product have a direct positive impact on sales of soft drinks. Javali (2011) factors affecting on both medical and oral expenditure in surveyed households in rural of Dhawad district, India. Duration of illness episode (in days) and total number of visits made to source of health care during the reference period are the main contributors to both medical and oral health care expenditure.

Deidra (1998) comparison of rural and urban students in the relationships of student ambition, achievement, and self-
concept. Student self-concept had a significant effect on both ambitions and achievement. There is no significant difference between rural and urban students in the relationships of student ambition, achievement, and self-concept. Zainun and Nadzirah (2013) factors affecting on demand of low-cost housing in Melaka. Economic factors include housing stock, inflation rate, and Gross Domestic Products (GDP) is the most significant indicators affecting the demand of low-cost housing.

Therefore, the aim of this research is to identify factors influencing on job satisfaction and to compare covariance-based structural equation modeling (CB-SEM) and partial least square-structural equation modeling (PLS-SEM) for modeling job satisfaction among lecturers.

II. RESEARCH METHODOLOGY

Structural equation model or SEM was developed as a unifying and flexible mathematical framework to specify the computer application (Byrne, 2001; Blunch, 2013). The numeric methods implemented in AMOS are among the most effective and reliable available (Arbuckle, 2012).

2.1 Covariance Based SEM (CB-SEM)

CB-SEM is one of the common and traditional methods used by researchers nowadays. Structural equation modeling (SEM) is increasingly a method of choice for concept and theory development in the social sciences, especially the marketing field (Hair et al., 2014). SEM also had been applied in medical area. Medical researchers now have powerful analytic tools to examine complex causal model with the development of SEM (Beren & Violato, 2010). Keller (2006) had examined behaviors that constitute risk of poor nutrition among seniors as part of a screening intervention.

The structural equation model framework can be summarized into three matrix equations, two for the measurement model component and one for the path model component (Grace, 2006). For the measurement model component,

\[ x = \Lambda_1 \xi + \delta \]  
\[ y = \Lambda_2 \eta + \epsilon \]  

where \( x \) is a \( p \times 1 \) vector of observed exogenous variables, and it is a linear function of a \( j \times 1 \) vector of exogenous latent variables \( \xi \) and a \( p \times 1 \) vector of measurement error \( \delta \). \( \Lambda_1 \) is a \( p \times j \) matrix of factor loadings relating \( x \) to \( \xi \). Similarly, \( y \) is a \( q \times 1 \) vector of observed endogenous variables, \( \eta \) is a \( k \times 1 \) vector of latent endogenous variables, \( \epsilon \) is a \( q \times 1 \) vector of measurement error for the endogenous variables, and \( \Lambda_2 \) is a \( q \times k \) matrix of factor loadings relating \( y \) to \( \eta \). Associated with equation 3.1 and eq. 3.2, respectively, are two variance-covariance matrices, \( \Theta_\xi \) and \( \Theta_\epsilon \). The matrix \( \Theta_\xi \) is a \( p \times p \) matrix of variances and covariance among measurement errors \( \delta \), and \( \Theta_\epsilon \) is a \( q \times q \) matrix of variances and covariance among measurement errors \( \epsilon \).

The path model component as relationships among latent construct variables can be written as:

\[ \eta = B \eta + \Gamma \xi + \zeta \]  

where \( B \) is a \( k \times k \) matrix of path coefficients describing the relationships among endogenous latent variables, \( \Gamma \) is a \( k \times j \) matrix of path coefficients describing the linear effects of exogenous variables on endogenous variables, and \( \zeta \) is a \( k \times 1 \) vector of errors of endogenous variables. Associated with eq. (3) are two variance-covariance matrices: \( \Phi \) is a \( j \times j \) variance-covariance matrix of latent exogenous variables, and \( \Psi \) is a \( k \times k \) matrix of covariance among errors of endogenous variables. With only these three equations, AMOS is a flexible mathematical framework that can accommodate any specification of a SEM model.

Model fitting is based on a fitting function that minimizes the difference between the model-implied variance-covariance matrix \( \Sigma \) and the observed variance-covariance matrix \( S \).

\[ min f(\Sigma, S) \]  

where \( S \) is estimated from observed data, \( \Sigma \) is predicted from the causal and no causal associations specified in the model, and \( f(\Sigma, S) \) is a generic function of the difference \( \Sigma \) between \( S \) and based on an estimation method that follows. As Shipley (2000) concisely stated, causation implies correlation; that is, if there is a causal relationship between two variables, there must exist a systematic relationship between them.

Hence, by specifying a set of theoretical causal paths, one can reconstruct the model-implied variance-covariance matrix \( \Sigma \) from total effects and unanalyzed associations. Bollen (1989) outlined a step-by-step formulation under the mathematical framework, specifying the following mathematical equation for \( \Sigma \):

\[ \Sigma = \begin{bmatrix} \Lambda_2 \Phi \Gamma' + \Phi \Psi \Phi \Lambda_2' + \Theta_\epsilon & \Lambda_2 \Phi \Gamma' \Lambda_1' + \Theta_\delta \\ \Lambda_2 \Phi \Gamma' \Lambda_1' + \Theta_\delta & \Lambda_2 \Phi \Lambda_2' + \Theta_\delta \end{bmatrix} \]  

where \( \Lambda = (I - B)^{-1} \). Note that in eq. (5) the derivation of \( \Sigma \) does not involve the observed and latent exogenous and endogenous variables (i.e. \( x, y, \xi \) and \( \eta \)).

A common method in SEM for estimating parameters in is maximum likelihood (ML). In ML estimation, the algorithm iteratively searches for a set of parameter values that minimizes the deviations between elements of \( S \) and \( \Sigma \) (Grace, 2006). This minimization is accomplished by deriving a fitting function, \( f(\Sigma, S) \) based on the logarithm of a likelihood ratio, where the ratio is the likelihood of a given fitted model to the likelihood of a perfectly fitting model. The maximum likelihood procedure requires the endogenous variables to follow a multivariate normal distribution, and \( S \) to follow a Wishart distribution. Hayduk (1987) described the steps in the derivation and expressed the fitting function \( F_{ml} \) as

\[ F_{ml} = \log |\Sigma| + \text{trace}(\Sigma^{-1}) - \log |S| - \text{trace}(S^{-1}) \]  

where \( \text{trace}(\cdot) \) refers to the trace of a matrix \( \Sigma \) and \( S \) are defined as above. Proper application of eq. (6) also requires that observations are independently and identically distributed and that matrices \( \Sigma \) and \( S \) are positive definite Hyduk (1987). After minimizing eq. (6) through an iterative process of parameter estimation, the final results are the estimated variance-covariance matrices and path coefficients for the specified model.

2.2 Partial Least Squares SEM (PLS-SEM)

PLS-SEM also known as Variance-Based SEM is also a useful and increasingly applied approach to examine structural equation models (Hair et al., 2012). The objective of PLS-
SEM is to minimize the amount of unexplained variance (maximizes the $R^2$ values). The estimation procedure for PLS-SEM is an ordinary least squares (OLS) regression-based method rather than the maximum likelihood (ML). PLS path models are formally defined by two sets of linear equations: the inner or structural model and the outer or measurement model. The inner model specifies the relationships between unobserved or latent variables, whereas the outer model specifies the relationships between a latent variable and its observed or manifest variables (indicators).

The inner model for relationships between latent variables can be written as:

$$\xi = B\xi + \zeta$$  

(7)

where $\zeta$ is the vector of latent variables, $B$ denotes the matrix of coefficients of their relationships, and $\xi$ represents the inner model residuals. The basic PLS design assumes a recursive inner model that is subject to predictor specification. Thus, the inner model constitutes a chain system (i.e. with uncorrelated residuals and without correlations between the residual term of a certain endogenous latent variable and its explanatory latent variables). Predictor specification reduces eq. (7) to:

$$\xi = B\xi$$  

(8)

PLS path modeling includes two different kinds of outer models: reflective (Mode A) and formative (Mode B) measurement models. The selection of a certain outer mode is subject to theoretical reasoning (Diamantopoulos & Winklhofer, 2001). The reflective mode has causal relationships from the latent variable to the manifest variables in its block. Thus, each manifest variable in a certain measurement model is assumed to be generated as a linear function of its latent variables and the residual $\varepsilon$:

$$X_x = \Lambda_x \xi + \varepsilon_x$$  

(9)

where $\Lambda$ represents the loading (pattern) coefficients. The outer relationships are also subject to predictor specification which implying that there are no correlations between the outer residuals and the latent variable of the same block that reduces eq. (9) to:

$$\xi = \Pi_{x}X_{x} + \varepsilon_x$$  

(10)

The formative mode of a measurement model has causal relationships from the manifest variables to the latent variable. For those blocks, the linear relationships are given as follows:

$$\xi = \Pi_{x}X_{x} + \varepsilon_x$$  

(11)

In the formative mode, predictor specification is also in effect, reducing eq. (11) to:

$$\xi = \Pi_{x}X_{x}$$  

(12)

The PLS algorithm consists of an iterative procedure of OLS regressions. The algorithms for estimating coefficients or weights can be written as follow:

**Step 1:** (initialization): Let the manifesting variables (MVs), $X_1, \ldots, X_k$ have mean ($X_0$) = 0 and $\text{VAR}(X_0)$ = 1. All weights are set equal to one. The latent variables (LVs) are scaled to have unit variance.

$$\hat{\Psi} = \hat{M}$$  

(13)

$$\hat{\gamma}_g = \frac{\gamma_g}{\sqrt{\text{VAR}(\eta_g)}}, \; g = 1, \ldots, G$$  

(14)

where $\hat{M}$ is the adjacency matrix and the LVs are initialized as $\hat{\Psi} = (\hat{\psi}_1, \ldots, \hat{\psi}_G)$

**Step 2:** The inner approximation comprises of estimating each LV as a weighted sum of its neighboring LVs. Here, the weights are recalculated based on the applied weighting scheme. The LVs are now computed again to ensure unit variance.

$$\hat{Y} = \hat{Y}E$$  

(15)

$$\hat{y}_g = \frac{\gamma_g}{\sqrt{\text{VAR}(\eta_g)}}, \; g = 1, \ldots, G$$  

(16)

The inner estimation is obtained by $\hat{\Psi} = (\hat{\psi}_1, \ldots, \hat{\psi}_G)$

**Step 3:** In outer approximation, initially all weights are set equal to one, and the weights are recalculated based on weighting scheme. The weights depend on the measurement mode; Mode A (Reflective measurement) and Mode B (Formative measurement). In Mode A, the block of MVs is the response and the LV is the regressor:

$$\hat{\omega}_g^T = (\hat{\psi}_1 \hat{\gamma}_g)^{-1} \hat{y}_g^T X_g$$  

(17)

$$= \text{COR}(\hat{\gamma}_g, X_g)$$

In Mode B, the multiple regression coefficient is written with the LV as the response and its block of MV as regressors:

$$\hat{w}_g = (X_g^T X_g)^{-1} X_g^T \hat{y}_g$$  

(18)

$$= \text{VAR}(X_g)^{-1} \text{COR}(\hat{y}_g, X_g)$$

**Step 4:** The factor scores are calculated. The outer weights vectors $w_1, \ldots, w_g$ are arranged in an outer weights matrix $W$. Eq.(19) and (20) result in the outer estimation of the latent variables, $\hat{Y} = (\hat{\gamma}_1, \ldots, \hat{\gamma}_G)$.

$$\hat{Y} = \hat{W}\hat{X}$$  

(19)

$$\hat{y}_g = \frac{\hat{y}_g}{\sqrt{\text{VAR}(\eta_g)}}, \; g = 1, \ldots, G$$  

(20)

**Step 5:** An iterative step. The estimation of the factor scores in Step 4 is taken to be final if the relative change of all the outer weights from one iteration to the next is smaller than a predefined tolerance.

$$\frac{w_{old} - w_{new}}{w_{old}} < \text{tolerance}$$  \hspace{1cm} \forall \; k = 1, \ldots, K, \; \text{and} \; g = 1, \ldots, G$$  

(21)

The weighting scheme is used for the estimation of the inner weights in Step 2 of the PLS algorithm. Jöreskog and Wold (1982) proposed the centroid weighting scheme. According to the weighting scheme using centroid, the matrix of inner weights $E$ is as follows:

$$e_{ij} = \begin{cases} \text{sign}(r_{ij}) & \text{for } c_{ij} = 1 \\ 0 & \text{elsewhere} \end{cases}$$  \hspace{1cm} i, j = 1, \ldots, G$$

(22)

### 2.3 Model Assessment

Schumacker and Lomax (2004) and Kline (2011) provided a comprehensive listing of indices and criteria to assess model fit, but four basic fit statistics are summarized here. The goal of model assessment is to test the causal implications of a model (Shipley, 2000).

2.3.1 Chi-square test: The first is the overall model chi-square test based on a test statistic that is a function of the mentioned fitting function $F_{ml}$ in eq. (6) as follows:

$$\chi^2 = (n - 1)F_{ml}$$  

(23)
where \( n \) is sample size and \( \chi^2 \) follows a chi-square distribution with degree of freedom \( df \). Subsequently, a \( p \) value is estimated and evaluated against a significance level.

2.3.2 Root mean square error of approximation (RMSEA), which is parsimony-adjusted index that accounts for model complexity. The index approximates a non-central chi-square distribution with the estimated non-centrality parameter as

\[
\delta_v = \max(\chi^2_v - df_v, 0)
\]

where \( \chi^2_v \) is computed from eq. 3.7 and \( df_v \) is defined above. The magnitude of \( \delta_v \) reflects the degree of misspecification of the fitted model. The RMSEA is then defined as

\[
\text{RMSEA} = \frac{\delta_v}{\sqrt{\frac{df_v(n-1)}}}
\]

2.3.3 Standardized root mean square residual (SRMR), which is relatively easy to compute. Both \( S \) and \( \Sigma \) are transformed into correlation matrices, and the residual matrix is the difference between the two. Hence the mean square of the elements in the residual matrix is the SRMR. In general, SRMR < 0.10 is considered a good fit of \( S \) as an approximation to \( \Sigma \).

2.3.4 Goodness of fit index (GFI): GFI is a measure of relative amount of variances and covariances jointly accounted for by the model, and it is defined as Jöreskog and Sörbom (1982)

\[
GFI = 1 - \frac{\text{trace}(\Sigma^{-1}S^{-1}I)}{\text{trace}(\Sigma^{-1}S^{-1})}
\]

where \( I \) is identity matrix. GFI ranged from 0 to 1.0 with 1.0 indicating the best fit.

III. RESULTS AND DISCUSSION

3.1 CB SEM

The standardized regression weights explained the relationship of the each items with variable. In Figure 4.4, it can be said that when Workload goes up by 1 standard deviation, Job Satisfaction goes up by 0.42 standard deviation. When Work-place Environment increase by 1 standard deviation, Job Satisfaction increase by 0.17 standard deviation. On the other hand, when Relationship with Colleagues increase by 1 standard deviation, Job Satisfaction goes up 0.23 standard deviation. Besides, as Management Style rises by 1 standard deviation, Job Satisfaction goes down by 0.25 standard deviation. When Promotional Opportunities goes up by 1 standard deviation, Job Satisfaction goes up by 0.16 standard deviation. Finally, as Remuneration goes up by 1 Standard deviation, Job Satisfaction rises by 0.14.

It is estimated that Job Satisfaction explains 47% (Estimate R^2) of its variance. The items that contribute to Job Satisfaction J1, J2, J4, J6 and J9 have error variance of 17%, 10%, 21%, 26% and 36% respectively.

Based on Figure 4.4, the correlation between latent construct Workload and Work-place Environment is estimated to be 0.299, it is indicates that the strength of the relationship between the two latent construct is slightly weak correlated. Next, the correlation between Workload and four constructs; Relationship with Colleagues, Management Style, Promotional Opportunities, and Remuneration are estimated to be 0.443, 0.293, 0.385 and 0.266 respectively. The correlation between
The latent construct Work-place Environment and two constructs namely Relationship with Colleagues and Remuneration is estimated to be 0.393 and 0.345 separately. This indicates that the strength of the relationship between the latent constructs are moderately weak correlated.

Besides, the correlation between Work-place Environment and other two constructs; Management Style and Promotional Opportunities are estimated to be 0.744 and 0.636 respectively. The correlation between latent construct Relationship with Colleagues and three constructs namely Management Style, Promotional Opportunities, and Remuneration are estimated to be 0.283, 0.387 and 0.198 separately. This shows that the relationship between the latent constructs are slightly weak correlated. However, the correlation between Promotional Opportunities and two constructs; Management Style and Remuneration are estimated to be 0.78 and 0.571 respectively. This indicates that the strength of the relationship between the latent constructs is moderately strong correlated. Lastly, the correlation between latent construct management Style and Remuneration is estimated to be 0.374, it is indicates that the strength of the relationship between the two latent construct is moderately weak correlated. Then, the further analysis is continued. This is achieved the requirement of discriminant validity which the correlation between each pair of latent independent (exogenous) construct should be less than 0.85 (Byrne, 2010).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate W</th>
<th>S.E</th>
<th>C.R</th>
<th>p-value</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workload</td>
<td>0.775</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Environment, E</td>
<td>0.345</td>
<td>0.867</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Colleagues, C</td>
<td>0.505</td>
<td>0.389</td>
<td>0.858</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Management, M</td>
<td>0.416</td>
<td>0.736</td>
<td>0.368</td>
<td>0.839</td>
<td></td>
</tr>
<tr>
<td>Promotional, P</td>
<td>0.429</td>
<td>0.601</td>
<td>0.416</td>
<td>0.727</td>
<td>0.820</td>
</tr>
<tr>
<td>Remuneration, R</td>
<td>0.295</td>
<td>0.411</td>
<td>0.193</td>
<td>0.442</td>
<td>0.526</td>
</tr>
<tr>
<td>Job Satisfaction, JS</td>
<td>0.553</td>
<td>0.434</td>
<td>0.521</td>
<td>0.402</td>
<td>0.518</td>
</tr>
</tbody>
</table>

Table 4.3: The regression weight for hypothesis in study

Table 4.4 presented the values of discriminant validity for PLS-SEM method. Discriminant validity value obtained from the square root of AVE value. The diagonal values (in bold) are the square root of AVE while other values are the correlation between the respective constructs. Fornell and Larcker (1981) stated the discriminant validity is achieved when a diagonal value bold is higher than the value in its row and column. Thus, the discriminant validity achieved since the diagonal value bold for seven constructs are greater than the value in its row and column.

3.2 PLS SE
3.2.1 Outer model

Based on both Figure 4.5 and Table 4.3, it can be concluded that, for every one unit increase in Workload, Job Satisfaction increases by 0.422 unit. Next, when Relationship with Colleagues goes up by 1 unit, so does Job Satisfaction by 0.152. However, Job Satisfaction would decreases by 0.152 with every 1 unit increase of Management Style. When Remuneration rises by 1 unit, Job Satisfaction increases by 0.086 units. The other relationships were found to be insignificant since the p-values were higher than 0.05.

The structural eq. model in CB-SEM is:

(i) Workload = W7 + 1.11W8 + W10
(ii) Work-place Environment = W2 + W3 + 0.92W7
(iii) Relationship with Colleagues = C2 + 0.98C3 + 1.11C4 + C5 + C7

The measurement models identified are:

(i) Job Satisfaction = 0.422 Workload + 0.222 Relationship with Colleagues – 0.152 Management Style + 0.086 Remuneration + e54

(iv) Work Satisfaction = J1 + 0.99J2 + 1.11J4 + 0.94J6 + 0.94J9

(v) Remuneration = R1 + 1.1R2 + 0.96R3 + 0.91R4

(vi) Management Style = M3 + 0.94M4 + 0.93M5 + 1.13M7 + M8

Table 4.4: Values for Discriminant Validity

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The coefficient of determination in Figure 4.8 is 0.471 for the Job Satisfaction endogenous latent variable. This means that the six latent variables (workload, work-place environment, relationship with colleagues, management style, promotional opportunities and remuneration) explain about 47.1% of the variance in job satisfaction.

3.2.2 Inner model

Table 4.5 shows the path coefficient, standard error and t-statistics of exogenous on endogenous construct once execute PLS algorithm and bootstrap. By inspecting through each row in Table 4.5, workload (0.301) is expected to be the highest effect on job satisfaction followed by promotional opportunities (0.243), relationship with colleagues (0.242), management style (-0.158), work-place environment (0.152) and remuneration (0.131). Furthermore, t-statistics was used as a guide to determine whether research hypothesis in this study will reject or accept. The path coefficient will be significant if the t-statistics is larger than 1.96 by using a two-tailed t-test with a significance level of 5% as suggested by Wong (2013).

The t-statistics (Table 4.5) for workload, relationship with colleagues, promotional opportunities and remuneration are 4.123, 3.259, 2.881 and 2.002 respectively. It was found that those factors have significant causal effect on lecturers’ job satisfaction. However, the other factors namely management style and work-place environment were found to be insignificant since the t-statistics was lower than 1.96.

Table 4.5: Path Coefficient, Standard Error and t-statistics for inner model

<table>
<thead>
<tr>
<th>Path</th>
<th>Path Coefficient</th>
<th>Standard Error</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workload -&gt; Job Satisfaction</td>
<td>0.3008</td>
<td>0.0730</td>
<td>4.1225</td>
</tr>
<tr>
<td>Work-place Environment -&gt; Job Satisfaction</td>
<td>0.1520</td>
<td>0.0818</td>
<td>1.8582</td>
</tr>
<tr>
<td>Relationship with Colleagues -&gt; Job Satisfaction</td>
<td>0.2420</td>
<td>0.0743</td>
<td>3.2585</td>
</tr>
<tr>
<td>Management Style -&gt; Job Satisfaction</td>
<td>-0.1577</td>
<td>0.0844</td>
<td>1.8684</td>
</tr>
<tr>
<td>Promotional Opportunities -&gt; Job Satisfaction</td>
<td>0.2427</td>
<td>0.0842</td>
<td>2.8814</td>
</tr>
<tr>
<td>Remuneration -&gt; Job Satisfaction</td>
<td>0.1308</td>
<td>0.0654</td>
<td>2.0018</td>
</tr>
</tbody>
</table>

In PLS-SEM, structural model is known as inner model. The collinearity among predictor constructs were examined before proceed to assessment of structural model. According to Hair et al. (2014), the path coefficients might be biased if the estimation involves significant levels of collinearity among the predictor constructs. The reason is the structural model in PLS-SEM is based on Ordinary Least Square (OLS) regression. The Variance Inflation Factor (VIF) values for workload, work-place environment, relationship with colleagues, management style, promotional opportunities and remuneration are 1.502, 2.322, 1.492, 3.072, 2.547 and 1.492 respectively.
1.432 sequentially. Those six factors have VIF values below 5 and it can be conclude that there is no collinearity occurred.

A bootstrapping procedure was executed to generate t-statistics for significance testing of both the inner and outer model. In this procedure, Hair et al. (2014) recommended a large number of subsamples (5000) are taken from the original sample with replacement to give bootstrap standard errors, which in turn gives approximate t-values for significance testing of the structural path. The Bootstrap result approximates the normality of data. Figure 4.9 presented the inner model after execution of Bootstrapping procedure.

3.3 Comparison between CB SEM and PLS SEM

To achieve the third objective, the CB-SEM and PLS-SEM were comparing during CFA. In CB-SEM, the items which have factor loadings lower than 0.6 were removed from the model and the unidimensionality was achieved as recommended by Zainuddin (2012). The items retained in the model as in Table 4.10.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Items</th>
<th>Factor Loadings</th>
<th>Factors</th>
<th>Items</th>
<th>Factor Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workload</td>
<td>W7</td>
<td>0.88</td>
<td>Management</td>
<td>M1</td>
<td>0.864</td>
</tr>
<tr>
<td></td>
<td>W8</td>
<td>0.782</td>
<td>Style</td>
<td>M2</td>
<td>0.842</td>
</tr>
<tr>
<td></td>
<td>W10</td>
<td>0.772</td>
<td></td>
<td>M3</td>
<td>0.884</td>
</tr>
<tr>
<td>Work-place Environment</td>
<td>V1</td>
<td>0.946</td>
<td></td>
<td>M4</td>
<td>0.709</td>
</tr>
<tr>
<td></td>
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<td></td>
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</tr>
<tr>
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<tr>
<td></td>
<td>V5</td>
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<td></td>
<td>M8</td>
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<tr>
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<td>0.834</td>
<td>Remuneration</td>
<td>R1</td>
<td>0.959</td>
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<td></td>
<td>R2</td>
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</tr>
<tr>
<td></td>
<td>C2</td>
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<td></td>
<td>R3</td>
<td>0.939</td>
</tr>
<tr>
<td></td>
<td>C3</td>
<td>0.899</td>
<td></td>
<td>R4</td>
<td>0.857</td>
</tr>
<tr>
<td></td>
<td>C4</td>
<td>0.831</td>
<td></td>
<td>R5</td>
<td>0.791</td>
</tr>
<tr>
<td></td>
<td>C5</td>
<td>0.874</td>
<td>Job</td>
<td>J1</td>
<td>0.901</td>
</tr>
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</table>
The indicators in CB-SEM which have outer loading below 0.6 was eliminated from the PLS-SEM model. Table 4.11 presented the outer loadings of indicators retained in the model. The researcher applied the same scale during unidimensionality procedure for both method to avoid biased comparison. However, the retained items or indicators in CB-SEM are not exactly same as in PLS-SEM. The comparison of factor or outer loadings still valid by comparing the similar items in both model. From both model, most the value of outer loading obtained in PLS-SEM is higher than CB-SEM.

Based on both criteria, it was found CB-SEM has lower factor loadings and AVE values compare to PLS-SEM. Thus, it can be conclude that PLS-SEM is appropriate to carry on the Confirmatory Factor Analysis which is more reliable and valid compared to CB-SEM.

Table 4.11: Outer loadings for indicators retained in PLS-SEM model

<table>
<thead>
<tr>
<th>Factors</th>
<th>Items</th>
<th>Outer Loadings</th>
<th>Factors</th>
<th>Items</th>
<th>Outer Loadings</th>
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<tbody>
<tr>
<td></td>
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<td>Workload</td>
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<td>M1</td>
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<td></td>
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<td>M2</td>
<td></td>
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<tr>
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<td>0.678</td>
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<tr>
<td></td>
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<td>M4</td>
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<tr>
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<td>M5</td>
<td></td>
<td>0.906</td>
</tr>
<tr>
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<td>R1</td>
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<tr>
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<td>R2</td>
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<td>R3</td>
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<td>R4</td>
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<td>V5</td>
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<td></td>
</tr>
<tr>
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<td>V6</td>
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<tr>
<td></td>
<td>V7</td>
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</tr>
<tr>
<td>Relationship with</td>
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<td>0.867</td>
<td>J1</td>
<td></td>
<td>0.885</td>
</tr>
<tr>
<td>Colleagues</td>
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<td>0.913</td>
<td>J2</td>
<td></td>
<td>0.901</td>
</tr>
<tr>
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<td>C3</td>
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<td>J3</td>
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<tr>
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<td>J5</td>
<td></td>
<td>0.856</td>
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<td>C6</td>
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<td>J6</td>
<td></td>
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<tr>
<td></td>
<td>C7</td>
<td>0.877</td>
<td>J7</td>
<td></td>
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<td>P3</td>
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<td>J10</td>
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</table>
Table 4.12: Average Variance Extracted values in CB-SEM and PLS-SEM

<table>
<thead>
<tr>
<th>Factors</th>
<th>CB SEM</th>
<th>PLS-SEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workload</td>
<td>0.661</td>
<td>0.601</td>
</tr>
<tr>
<td>Work-place Environment</td>
<td>0.771</td>
<td>0.752</td>
</tr>
<tr>
<td>Relationship with Colleagues</td>
<td>0.698</td>
<td>0.736</td>
</tr>
<tr>
<td>Management Style</td>
<td>0.67</td>
<td>0.704</td>
</tr>
<tr>
<td>Promotional Opportunities</td>
<td>0.714</td>
<td>0.672</td>
</tr>
<tr>
<td>Remuneration</td>
<td>0.829</td>
<td>0.861</td>
</tr>
<tr>
<td>Job Satisfaction</td>
<td>0.626</td>
<td>0.676</td>
</tr>
</tbody>
</table>

### IV. CONCLUSION

From the results obtained, it is found that the Workloads, Relationship with Colleagues, Management style and Remuneration factors have significant effect on Job Satisfaction among lecturers in UTHM using CB-SEM. However, the Work-place Environment and Promotional Opportunities do not significantly effect on Job Satisfaction since the \( p \)-value was exceed 0.05. In PLS-SEM, there are four factors namely Workloads, Relationship with Colleagues, Promotional Opportunities and Remuneration have significant effect on Job Satisfaction among lecturers in UTHM. Meanwhile, the other two factors do not have significant causal effect on lecturers’ job satisfaction since the \( t \)-statistics below 1.96. For moderating effect in CB-SEM, the researcher concluded gender and years of teaching have moderates effect on relationship between all significant factors and lecturers’ job satisfaction. In PLS-SEM, only gender has moderates effect on relationship between Relationship with Colleagues and Job Satisfaction. Furthermore, the factor (outer) loadings and AVE values in PLS-SEM is higher than CB-SEM during Confirmatory Factor Analysis stage. Hence, it can be conclude that PLS-SEM is appropriate to carry on the Confirmatory Factor Analysis which is more reliable and valid.

### REFERENCES


[35]