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ModelingStructural Model for Higher Order Constructs (HOC) Using Marketing Model

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Abstract: Analysis of Moment of Structures (AMOS) is one of the prominent software developed for Covariance-Based Structural Equation Modeling (CBSEM). AMOS is popular since it is more flexible than other statistical packages. Historically, this software was developed by Jim Arbuckle in 1995 and is widely employed by academicians since then. This software has become even more popular after distributor IBM distributes itworldwide with SPSS where Amos is one of its applications. Consequently, higher education institutions subscribing SPSS have AMOS automatically; and they areadopting the CBSEM technique. Although an enormous number of journal articles are being published using CBSEM, a number of instructional materials for researchersto follow are still limited especially in addressing the Higher Order Constructs (HOC). This paper intends to address this knowledge gap and help researchers to understand properly how to address HOC in their work. The paper outlines properguides for application and the interpretation of report for researchers to follow.

Key words: AMOS · Higher Order Model (HOM) · Marketing

INTRODUCTION

Structural Equation Modeling (SEM) is increasingly a method of choice for theory testing and theory development [1]. SEMhas been established as a second generation method of multivariate analysis. The methods are often used in tourism research [2], in marketing [3], in management [4] and also insocial sciences and beyond. With SEM, the researchers can model the complex inter-relationshipsamong the constructs by taking into consideration the measurement errors of the items andthe residual for every equation.Due to the advent of various statistical packages such as AMOS, LISREL, MPLUS, EQS, Lavaan and OpenMx, the researchers have more choices to employ foranalyzingtheir complex models. Among the statistical packages that embrace CBSEM, AMOS software is considered the most popularchoice since it is user-friendly and high attractiveness compared to others [5], [6]. More importantly, it is being distributed by IBM worldwide through IBM-SPSS. Thereby, most researchers in higher learning institutions are employing CBSEM for modeling and estimating the inter-relationships among constructs in the model concurrently.

Although the statistical package for CB-SEM was perceived beneficial to the applied researchers, still there are many researchers who fail to employthe method properly especially when dealing with Higher Order Constructs (HOC). Novice researchers, for example, are making mistakes when integrating theexogenous and endogenous constructswhich consist of HOC. The mistakes could occur as early as validating the measurement model forHOC in Confirmatory Factor Analysis (CFA) [7]. Therefore, the purpose of this paper is to provide aninsight for thereadersto model and analyze HOC for both stages of (SEM) namely the measurement and the structural models. Meanwhile, the guidelines for drawing HOCarealso presented to facilitate the researchersto understandproperly regardingthe concept of HOC in CBSEM.

Nature of Structural Equation Modeling (SEM): There are two models involved in Structural Equation Modeling (SEM) namely the measurement model which specifies the relationship between latent construct and its respective measuring items [8], [9], [10], [11] and the structural model which specifies the inter-relationship between latent constructs involved in the study. In CBSEM, the

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requirement to validate the measurement model of the constructs is necessary to ensure the constructs are valid and reliable before moving to the next phase namely SEM. The validation procedure formeasurement model of latent constructs in CBSEM is carried out through Confirmatory Factor Analysis (CFA). In this phase, the researchers need to assess the measurement model of latent constructs for unidimensionality, validity and reliability [8], [9], [10], [11]. The CFA approachwould compute the factor loading for every item measuring first order constructs, the factor loading for every component measuring the second order constructs and theoverall fitness indexes of the model. CFA would also compute the correlation between latent constructs in the model. Using the factor loadings, the researcher could compute the Average Variance Extracted (AVE) which determines the convergent validity of the constructs as well as computing the Composite Reliability (CR) for every construct. CR reflects the extent of the reliability of the respective construct. Thus, by examining the fitness indexes, the researcher could assess the construct validity [8], [9], [10], [11]. In accordance to [12], the measurement model could be declared fit if the measurement model for the constructs is compatible with the data from the field. In this case, compatibility means construct validity where it can be assessed through a set of fitness indexes. The convergent validity could be assessed using AVE and by developing the discriminant validity index summary, the researcher could determine the discriminant validityof the constructs.

As far as latent constructs are concerned, the researchers might have severalitems measuring their first order constructs as well as several components measuring their second order constructs, where each component also consists of several items [8]. When running CFA to validate the constructs, the researchers need to determine the correlation between the constructs regardless of whether they are first order or second order construct. The researchers do not need to worry about the correlation between components measuring the second order construct since unlike the first order constructs, the components in second order constructs are not the constructs in the first place. Furthermore, there be a high correlation between components; the problem will be reflected in the fitness indexes of the overall model. Thus, it is advisable for the researchers to employ the pooled-CFA since it is fast, efficient and could avoid the identification problem when certain construct has less than four measuring items [13], [14], [5].

The second model involves in SEM is called structural model. Once the validation procedure of CFA is completed and the measurement model of all latent constructs achieved unidimensonality, validity and reliability, the researchers need to assemble these constructs in a structural model. Beginning with exogenous constructs on the left, followed by the mediators in the middle (if any) and ended with the endogenous constructs at the right. The linkages between constructs in the model should follow exactly the research framework and the stated hypotheses to be tested. If the exogenous construct is hypothesized to have a causal effect on an endogenous construct, then a single headed arrow should flow from an exogenous pointing out to the endogenous construct. Meanwhile, the mediator construct could be endogenous in the relationship between exogenous and mediator; and it could also be exogenous in the relationship between the mediator and endogenous construct. If the study has more than one exogenous construct, these constructs should be linked using the double headed arrow to assess the correlation between them. Lastly, the endogenous construct should have one residual term so that the error in equation could be estimated [15]. The structural model emerged is substantive to estimate the direct effect between the exogenous construct and endogenous construct, it is also efficient for estimating the indirect effect between exogenous construct and endogenous construct through a mediator construct [16].

In CBSEM, there are two estimators accepted for normal theory estimator namely the maximum likelihood and generalized least square estimator [17]. Among of these two normal theory estimators, the maximum likelihood estimator is always being preferred since it is more robust than the generalized least square estimator.

Modeling the HOC: An example of Marketing Model: The following example is obtained from a marketing model which consists of HOC [18]. The study will use this model to demonstrate the modeling and analysis of the measurement as well as structural model using Amos Graphic. In the first place, the authors present the theoretical framework being developed based on solid literature. In this paper, we testedfourexogenous constructs (A, B, C, D), one mediator construct (M) and one endogenous construct (Y) as shown in Figure 1.

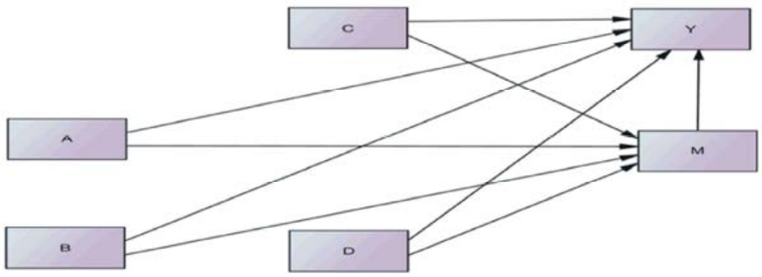

Fig. 1: The Theoretical Framework of the study

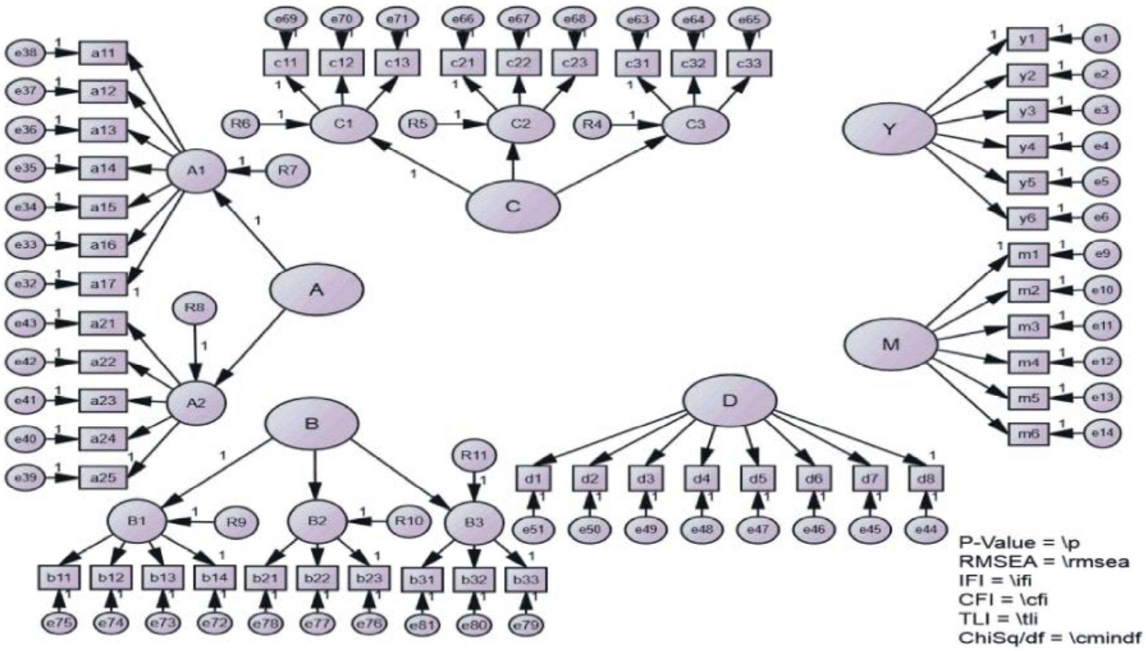

Fig. 2: Specification of measurement model

Based on Figure 1, there are four exogenous constructs namely A, B, C and D with their single-headed arrow pointing to mediator construct (M) and an endogenous construct (Y). The three exogenous constructs in the model namely A, B and C are higher order constructs HOC). While the other two constructs (mediator and endogenous) are first order.In this case, construct A is measured using 2 dimensions, construct B and C are measured using three dimensions respectively. The remaining construct namely constructD, construct Y and construct M are first order constructs. In structural equation modeling, there are two steps involved in the analysis namely validating the measurement model of the constructs and modeling the structural model [2]. In the first step, the researchers need to perform the Confirmatory Factor Analysis (CFA) procedure to validate the constructs. And in the second step, the researchers need to assemble the validated constructs in the structural model to execute Structural Equation Modeling (SEM). In this example, the researchers will employ the Pooled-CFA where all constructs are pooled together and the CFA procedure is executed at once for all constructs (both first order and HOC).

Ideally, the researcher should assemble the constructs as shown in Figure. Begin with exogenous constructs (A, B, C and D), followed by the mediator construct (M) and ending with the endogenous construct (Y). The constructs, the components and the measuring items are drawn accordingly. One of the arrows pointing to the components (HOC) must be given a parameter “1” as a reference point for Amos to compute the factor loading. In addition, the components where the single headed arrows are pointing at must have a residual (Figure 2).

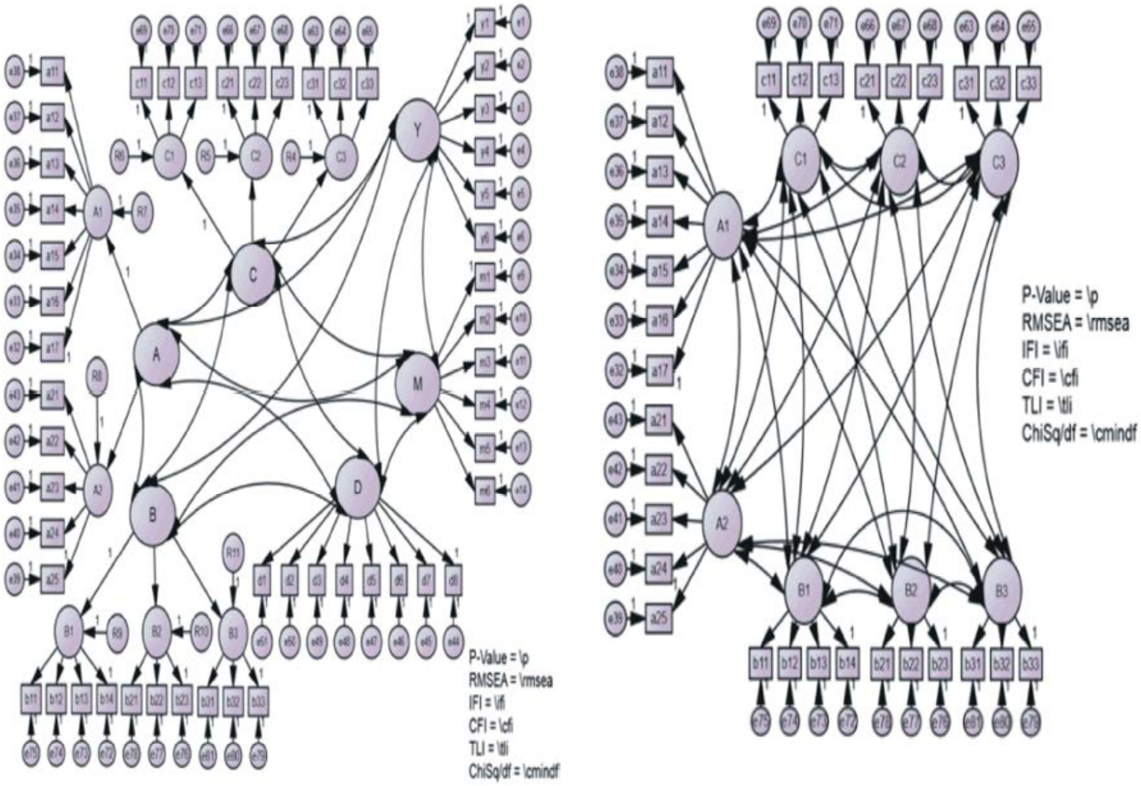

Fig. 3a: The Correct Pooled-CFA

Fig. 3b: The Incorrect Pooled-CFA

Fig. 3: The Correct and Incorrect of Pooled CFA

In this study, the instrument employed the 10-point interval scales ranging from (1) strongly disagree to (10) strongly agree. The 10-point interval scales were preferred since the data obtained using this scale meets the requirement for parametric analysis of "independence"where the respondents are given wider choice to state their perception [7], [19].

Finally, all constructs must be linked together using the double headed arrow to estimate the correlation between them. The double headed arrows should link the constructs only and not the components (Figure 3). Since the components measuring HOC are not considered the constructs, the correlations between components should not be permitted in the measurement model. This particular mistake is normally committed by a novice researcher (Figure 3b).

In order to provide more explanation on the modeling of HOC, we create both models as shown in Figure 3 to illustrate between the correct and the incorrect modeling of HOC. In the correct Pooled-CFA perspectives, the double-headed arrows are linking the constructs (first order and second order). In contrast, the incorrect Pooled-CFA linked the double headed arrow between first order constructs and the components of HOC.As has been said earlier, still there are many researchers who are ignorant and still practice such modeling.

In modeling the HOC, the researchers need to rely on the theoretical perspective governing the constructs whether that particular construct is a first order or higher order (HOC). Normally the results of Exploratory Factor Analysis (EFA) would tell. The FA was carried out to determine the dimensionality of items measuring the construct.In the pilot study, the researchers may be interested to determine the components and items retained in the model.

The measurement model in Figure 3a has been executed and the output is shown in Figure 4. Using the results obtained in Figure 4, the researcher could assess the output in determining the unidimensionality, validity (construct validity, convergent validity and discriminant validity) and Reliability (Composite Reliability).

Testing Measurement Model

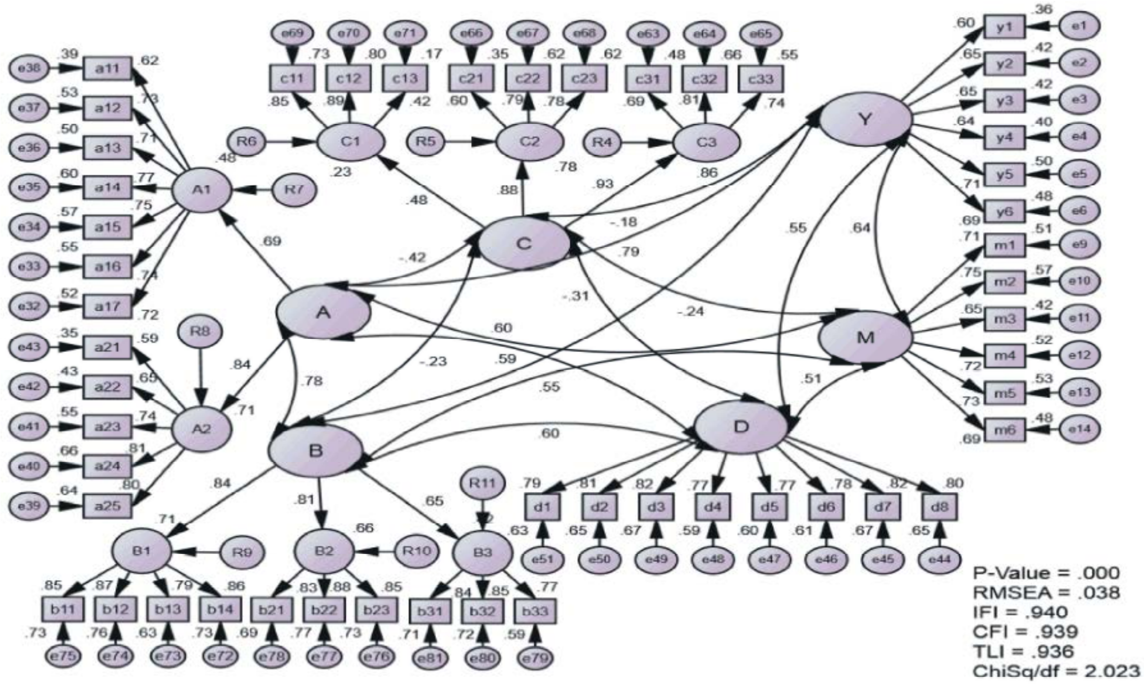

Fig. 4: The Pooled-CFA for Validating the Measurement Model of Latent Constructs

Figure 4 shows that the correlation coefficient and the fitness index. In this study, the authors prefer RMSEA, IFI, CFI, TLI and Chisq/df as the minimum requirement of fitness index to determine fitness for each measurement model.As such, the result of fitness index can be derived by AMOS output at model fit. In structural equation model, the assessment of measurement model should be testing isolated such that the researchers capable of to specify the model to be more fit. In traditional procedure, the fitness index can be upgraded into more quality that is by removal of low indicator loadings. Actually, there are manyrules of thumb for removal of indicator when performing the Confirmatory Factor Analysis (CFA) such as 0.40, 0.50 and 0.60 of factor loadings. Nevertheless, we suggest the researchers choose 0.60 of factor loadings as the minimum loadings in the model as always anticipated by previous research [9], [20], [21], [14], [22]. Because the high factor loadings will guarantee the investigators to capture more variances in the model that can be measured through Average Variance Extracted (AVE) [23].

In terms of the goodness of fit, the model will be declared a good fit if the chi-square normalized by degree of freedom was less than 5.0 [24], [25], [26], [18], [27] and it was claimed as the best measure of fit to examine whether the model being tested under satisfactory or unsatisfactory level. In AMOS application, the chi-square test can be known as 'cmin' and it can be appropriate when integrated with maximum likelihood estimator [28] as follows:

$$\begin{aligned} f_{ML}\left(\mu^{(g)},\Sigma^{(g)};\bar{\mathbf{x}}^{(g)},\mathbf{S}^{(g)}\right) &= f_{KL}\left(\mu^{(g)},\Sigma^{(g)};\bar{\mathbf{x}}^{(g)},\mathbf{S}^{(g)}\right)-f_{KL}\left(\bar{\mathbf{x}}^{(g)},\mathbf{S}^{(g)};\bar{\mathbf{x}}^{(g)},\mathbf{S}^{(g)}\right) \\ &= \log\left|\Sigma^{(g)}\right|+\mathrm{tr}\left(\mathbf{S}^{(g)}\Sigma^{(g)^{-1}}\right)-\log\left|\mathbf{S}^{(g)}\right|-p^{(g)}+\left(\bar{\mathbf{x}}^{(g)}-\mu^{(g)}\right)'\Sigma^{(g)^{-1}}\left(\bar{\mathbf{x}}^{(g)}-\mu^{(g)}\right). \end{aligned} \tag{1}$$

For maximum likelihood estimation, Equation (1) has a chi-square distribution for correctly specified models under appropriate distributional assumptions. However, the formula can be exhibit some inconsistencies in finite samples where the researchers supposed to split the sample into two sub-groups that is obvious have unequal of sample size. In this case, the researchers capable of handling the moderator analysis by comparing each model simultaneously.Furthermore, the formula for other fitness indexes also presented as follows:

$$\mathrm{CFI} = 1 - \frac{\max\left(\hat{C} - d, 0\right)}{\max\left(\hat{C}_b - d_b, 0\right)} = 1 - \frac{\mathrm{NCP}}{\mathrm{NCP}_b} \qquad (2)$$

$$\mathrm{TLI} = \rho_2 = \frac{\frac{\hat{C}_b}{d_b} - \frac{\hat{C}}{d}}{\frac{\hat{C}_b}{d_b} - 1} \qquad (3)$$

$$\mathrm{IFI} = \Delta_2 = \frac{\hat{C}_b - \hat{C}}{\hat{C}_b - d} \qquad (4)$$

$$\mathrm{RFI} = \rho_1 = 1 - \frac{C/d}{\hat{C}_b/d_b} = 1 - \frac{F/d}{\hat{F}_b/d_b} \qquad (5)$$

$$\mathrm{NFI} = \Delta_1 = 1 - \frac{\hat{C}}{\hat{C}_b} = 1 - \frac{\hat{F}}{\hat{F}_b} \qquad (6)$$

Equation (2), (3), (4), (5)and (6) were classified under the same category that is incremental fit index. In accordance to [29], the researchers supposedly choose at least one of the incremental fitindex to assess the fitness of each measurement model. In incremental fit of structural equation model, there are numerous fitness index such as CFI [24] or RNI (McDonald & Marsh, 1990), TLI or NNFI [30], [31], IFI [13], RFI [30] and NFI [31]. Strictly speaking, all the best measure of incremental of fit are above 0.90 since the value would fall in the range between 0 and 1. The incremental fit value approaching to 1 indicates as a best fit [6]. Next, we address the category of absolute fit. RMSEA.

$$\mathrm{LO\ 90} = \sqrt{\frac{\delta_L/n}{d}}, \ \mathrm{HI\ 90} = \sqrt{\frac{\delta_U/n}{d}} \qquad (7)$$

Most of the published papers prefer RMSEA as the main choice under absolute fit. It was suggested that a value of the RMSEA below 0.05 would indicate a close fit of the model in relation to the degree of freedom [32]. opined that a value of about 0.08 or lower for the RMSEA would indicate a reasonable error of approximation and never employ a model with a RMSEA higher than 0.10. It cannot be regarded as infallible model if the exact value RMSEA = 0.0, yet, it becomes the main arsenal if the study involved consistingabundance number of observed and unobserved variables. Since not all the fitness indexes can succeed when the structural model is multifaceted. Once the fitness requirements were achieved, then, the researchers can summarize the result for convergent and discriminant validity as it is prior to examining the reliability and validity of each latent variables (Refer to Table 1, Table 2 and Table 3).

Since this study contains the higher-order construct, the serial examination on their convergent validity must be explicitly reported as exhibited in Table 1 and Table 2. The results in Table 1 shows all Composite Reliability (CR) and Average Variance Extracted (AVE) exceeds the threshold value of 0.6 and 0.5 respectively which indicate the achievement of convergent validity and composite reliability of all main constructs in the model [8], [9]. Furthermore, the results in Table 2 shows all CR and AVE exceeds the required value of 0.6 and 0.5 respectively which indicate the achievement of convergent validity and composite reliability of all sub-constructs in the model [6], [33]. The study needs to assess the discriminant validity for all main constructs involved in the model. Thus, the discriminant validity index summary is computed as shown in Table 3.

Table 3 shows the Discriminant Validity among the constructs is achieved since all diagonal values are higher than the values in rows and columns. The diagonal values are the square root of the AVE (Average Variance Extracted) for the respective construct and other values are the correlation between the respective constructs in the measurement model. Based on the above report, the constructs in the model have achieved the discriminant validity [9], [1]. Based on the proposed hypotheses to be tested, the construct is linked from an exogenous construct to the respective endogenous construct using the single header arrow. Next, the path model was performed as the research hypotheses proposed.

An Example of the Hypothesized Model: As we can understand the relationship of latent variables in Figure 5, there are 4 exogenous latent constructs have a single arrow pointing out to the other latent variable of M and Y. All these exogenous variables need covariate each other to represent the correlation between exogenous construct. Each correlation must be included in the model as it is necessary to satisfy the parametric assumptions and so the equations. Meanwhile, latent construct M is a mediator where plays a role as the intervening variable that is become an exogenous and endogenous construct at the same time in determining the path estimates of structural model. Therefore, the latent construct M also

Table 1: Main Construct (First Order)

Construct	Item	Factor Loading	CR (above 0.6)	AVE (above 0.5)
A	A1	.69	**.741**	**.591**
	A2	.84		
B	B1	.48	**.823**	**.623**
	B2	.88		
	B3	.93		
C	C1	.84	**.813**	**.595**
	C2	.81		
	C3	.65		
D	d1	.79	**.932**	**.632**
	d2	.81		
	d3	.82		
	d4	.77		
	d5	.77		
	d6	.78		
	d7	.82		
	d8	.80		
M	m1	.71	**.858**	**.503**
	m2	.75		
	m3	.65		
	m4	.72		
	m5	.73		
	m6	.69		
Y	y1	.60	**.870**	**.532**
	y2	.85		
	y3	.65		
	y4	.84		
	y5	.71		
	y6	.69		

Table 2: Sub-Construct (Second Order)

Construct	Item	Factor Loading	CR (above 0.6)	AVE (above 0.5)
A1	a11	.68	.892	.542
	a12	.78		
	a13	.71		
	a14	.77		
	a15	.75		
	a16	.74		
	a17	.72		
A2	a21	.59	.844	.523
	a22	.65		
	a23	.74		
	a24	.81		
	a25	.80		
B1	b11	.85	.908	.711
	b12	.87		
	b13	.79		
	b14	.86		
B2	b21	.80	.881	.712
	b22	.88		
	b23	.85		
B3	b31	.84	.861	.674
	b32	.85		
	b33	.77		
C1	c11	.85	.777	.558
	c12	.88		
	c13	.42		
C2	c21	.60	.770	.531
	c22	.79		
	c23	.78		
C3	c31	.69	.792	.560
	c32	.81		
	c33	.74		

exert on the latent variable Ysince it is actually the endogenous construct of structural model. Please keep in mind that the observed variable in a model must perceive have a high loading. Because the factor model hypothesizes that the variance of a set of observed variable can be perfectly explained by the existence of one unobserved variable (latent construct) and individual random error (measurement error; [12]).

Table 3: The Discriminant Validity Index Summary

	A	B	C	D	M	Y
A	**.80**					
B	.43	**.78**				
C	.78	.25	**.79**			
D	.59	.32	.60	**.79**		
M	.60	.23	.55	.51	**.71**	
Y	.79	.17	.78	.55	.64	**.80**

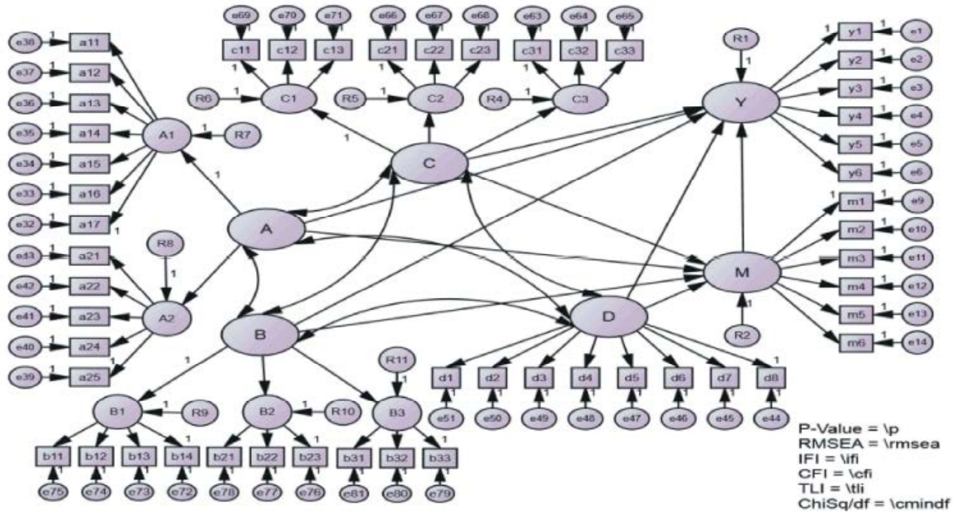

Fig. 5: Modeling the Inter-relationships among Constructs in the Structural Model

Testing the Hypothesized Model

Standardized Estimate

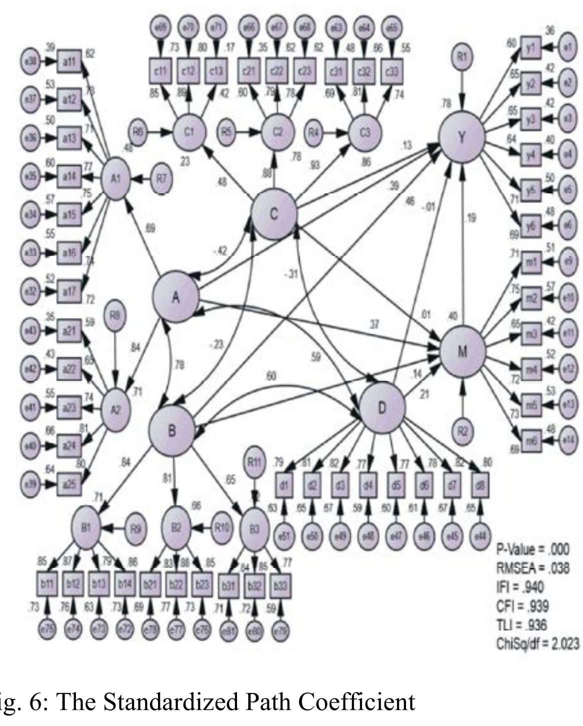

Fig. 6: The Standardized Path Coefficient

Unstandardized Estimate

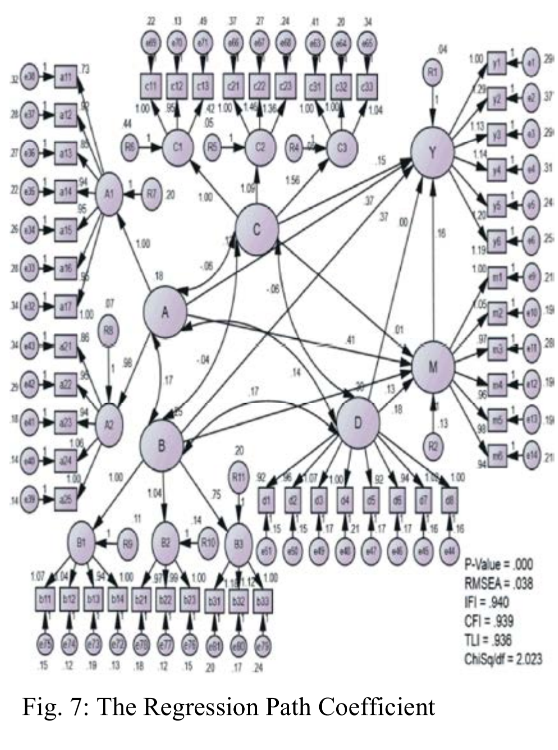

Fig. 7: The Regression Path Coefficient

Table 4: The Regression Path Coefficient and its Significance

			Estimate	S.E.	C.R.	P	Results
M	<---	D	.176	.043	4.086	***	Significant
M	<---	C	.011	.061	.187	.852	Not Significant
M	<---	A	.406	.117	3.480	***	Significant
M	<---	B	.135	.085	1.584	.113	Not Significant
Y	<---	C	.147	.046	3.161	.002	Significant
Y	<---	A	.367	.092	4.000	***	Significant
Y	<---	B	.366	.066	5.554	***	Significant
Y	<---	D	-.004	.031	-.140	.888	Not Significant
Y	<---	M	.164	.039	4.240	***	Significant

The value for each path estimates, covariance and measurement error are obtained when the researchers tick unstandardized estimates and standardized estimate at the 'Analysis Properties'. In generals, unstandardized estimates is frequently being reported as the researchers intend to test their research hypotheses that is based on the significant of path estimates as presented in Table 4.

Based on the finding revealed in Table 4, latent variable A, B, C and M have a high significant impact on latent variable Y. Among of them, latent variable A was perceived as the most importance factor due to carry high estimate compare to others. Meanwhile, latent variable A and D have a high significant impact on latent variable M. Since this study adopt the existence of one unobserved of mediator variable, the testing of mediation effect is required. Based on this, we adopt the strategy of using Baron and Kenny approach to determine the significant of mediation effect. Accordingly, the mediation effect was exist if the indirect effect are significant (refers [14]). In this case, the latent variable A and D have significant impact on latent variable M and then latent variable M has significant impact on latent variable Y. Finally, it can be concluded that latent variable M mediates two relationships that is from latent variable A to latent variable Y and from latent variable D to latent variable Y. Additionally, type of mediation can be determined based on the significant effect of direct effect or causal effect (from exogenous to endogenous construct). If the non-significant effect of direct effect occurred, then, it can be stated that full mediation was considered. In contrast, the partial mediation was considered when the significant effect of direct effect occurred. In this case, latent variable M was considered as partial mediation in the relationship between latent variable A and latent variable Y. Meanwhile, latent variable M was considered as full mediation in the relationship between latent variable D and latent variable Y.

CONCLUSION

This paper has discussed the use of a second generation multivariate methodology called structural equation modeling for marketing model, with a focus on conventional or covariance based structural equation modeling which is an extended method to regression analysis and principle axis factoring. A simulated marketing model is presented using the AMOS 21.0 application to help the marketers, beginners, researchers, academician and practitioners excel the basics of CB-SEM quickly in a proper explanation begin with the measurement model until the final stage. This paper is more focus on the higher order construct as it is become one of the high demand in data analysis recently. Using this, the researchers manage to specify their model in the right track so that the result obtained for managerial decision is valid. Nevertheless, this study is limited for the implementation of higher order construct model and still need improvement for the other type modeling such that the researchers will be more understanding. Advanced users who want to explore the field of conventional structural equation modeling can refer to the works of other books written by [21], [9], [34], [35].

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