Research Article

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CB-SEM vs PLS-SEM Method for Traffic Characteristic at Road Intersection in Mixed Traffic Condition

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Abstract

The aim of this study is to compare recently used methods of Structural Equation Modelling (SEM) which consists Covariance Based Structural Equation Modeling (CB-SEM) and Partial Least Squares based Structural Equation Modelling (PLS-SEM). The concept behind the first approach method is based on covariance, meanwhile the second approach is based on variance (partial least squares). First, the study develops CB-SEM by using eight hundred forty-one data set from right turn motor vehicle (RMV) in mixed traffic road network. Next, it further analyses the difference between PLS and Consistent PLS algorithms and finds the same result in both methods. Consequently, structural model is tested using CB-SEM and PLS-SEM. The outcomes indicate that the item loading is typically higher in CB-SEM than PLS-SEM. Model fit indices in CB-SEM have a better measurement, whereas PLS-SEM fit indices are still applying and less than CB-SEM. In PLS-SEM contribute excellent combine-based models, whereas CB-SEM are better for factor-based models. The comparison between both methods by providing visualization mapping diagram with numerical and empirical may contribute to existing literature as well as for predictive research domain.

Keywords: Covariance Based Structural Equation Modelling (Cb-Sem), Partial Least Squares Based Structural Equation Modelling (Pls-Sem)

1. Introduction

Structural Equation Modelling (SEM) is typically applied to describe multiple regression analysis via visualization mapping and model validation. It has an advantage to connect every observed variable, un-observed variable, loading factor and latent factor in one mapping diagram and simultaneously verify the model through model fits. It has capability to analysis complex models by integrating all the dataset in one mapping diagram. SEM is an improvement from the previous traditional linear modelling technique such as Analysis of Variance (ANOVA), multiple regression analysis and logistic regression method. It is also defined as the combination of multiple linear analyses and factor analyses concurrently [1-3]. SEM focus to recognize the connection between latent constructs (factors) that are typically specified by several measures This method also recognizes as covariance structure analysis as well as latent variable analysis. SEM system is more on a confirmatory concept rather than an exploratory factor analysis. It has unique feature and can be summarized as follows: Latent Factors are define based on dependence relationships and usually identify as constructs [4]. The complex model in SEM consists various independent and dependent relationships among the constructs. It has a method with detailed analysis of various covariance statistics such as mean, standard deviation, coefficient, t-Statistic used to analysis the covariance between the observed variables. Lately, the PLS method has been widely applied in various disciplines among the researchers due to its variance-based relationship rather than covariance [5-8]. Traditional methods like multivariate techniques that focus only individual objectives as compared to SEM that can analyse more than one model simultaneously. In SEM, to find the most appropriate relationship among the latent factors is by validating the alternate models. It typically has ability to conduct with a large sample [8-9].

The structure of this paper is organized as follows. Section 2 describes about methodology of the study. Section 3 discusses fit indices use in SEM. Section 4 concentrates Covariance Based Structural Equation Modelling CB-SEM, Partial Least Squares

Based Structural Equation Modeling (PLS-SEM) Algorithm, Consistent PLS-SEM, relationship among the construct and comparison of model fit three models. Section 5 provides the discussion and lastly Section 6 is the conclusion of the study.

1.1 Measurement model and path analysis in SEM

Recently SEM has become a favourite analytic tool especially in social science, engineering, and technology [6,9]. It is because this method has capability to measure experimental and nonexperimental dataset. The combination of complex theoretical model developed by applying this method is usually chained with the data collected to be analysed and validated. This chained is identified as model-data fit. This kind of fitness represents empirical data to evaluate the theoretical model. Typically, SEM requires a large sample data and at less a minimum data of 200 sample. In this study SEM evaluates two models: measurement model and path analysis.

1.2 Measurement Model

Measurement of these unobserved variables was discussed first before defining the analysis among the latent variables (constructs/factors). Latent variables or constructs are derived from calculated observed variables and it cannot be measured directly. Each latent factor or indicator is measured by observed items that are tested for validity and reliability. The measurement model in SEM was assessed using Confirmatory Factor Analysis (CFA) [10,8]). Exploratory Factor Analysis (EFA) is different from Confirmatory Factor Analysis (CFA), it functions to validate factor specification by visual calculate empirical data. To validate the measurement for CFA is by using Model Fit. The path model among latent factors is verified after model fit is assessed.

1.3 Path Analysis

The concept behind path model is based on multiple regression that is estimated simultaneously. It can be interaction relationship, moderation as well as mediating among the observed predictors. The development of structural relationship among the latent predictors is established connecting observed predictors. The path typically can be in the form of covariance-based or causal. Furthermore, CFA is used to validate the measurement models of the latent constructs. It is recommended to conducted CFA first for all the factors before connecting the relationship among them [6,7,11].

2. Methodology

This study is carried out using a quantitative analysis considering traffic characteristic, approach speed, vehicle classification, type of conflict, vehicle gap, infrastructure, and right-turn motor vehicle. A dataset of 841 for right-turn motor vehicles which consists (480 rejected gaps and 361 accepted gaps). The Federal Route 50 located in south peninsular of Malaysia was selected in this case. The design of this infrastructure which has four-lane, two-carriageway with design speed of 100 kph. In year 2024, it has capacity of receiving approximately more than 92,000 veh/day or 9,100 veh/hr. The data collection using video camera at eleven blackspots area has been accomplished and the microscopic analysis of the traffic behaviour is executed at the laboratory. The detail of each variables involved are provided in Table 1. In early stage, the authors conduct the exploratory factor analysis (EFA) to identify the factor. The EFA suggest six factors to explain the variance in the model. These factors are named as SL (Speed Limit), VC (Vehicle Classification), Infra (Infrastructure), TC (Traffic Conflict), VGap (Vehicle Gap) and RMV (Right-turn Motor Vehicle). SL has seven items [12]: speed limit less than 40 and so on (SPLT 40, SPLT 45, SPLT 50, SPLT 53, SPLT 57, SPLT 60). VC has five items [13]: passenger car, rider, pillion, lorry, van. TC has two items [14]: rear-end conflict angular conflict (REc, AGc). Infra has two items [15]: channelization and traffic light (Chlzation, Tlight), Vgap has one (Gap) and RMV has one [16]: right-turn. Both AMOS and Smart PLS are used to analyse the conceptual diagram with empirical data. First, the authors apply the CB-SEM using IBM-SPSS-AMOS program as the basic idea and is verified with PLS-SEM with the help of Smart PLS software as the final model. The comparative analysis in this study, we use IBM® SPSS® Amos version 23 and Smart PLS 4.0.9.9.

Abbr.	Description
RMV	RMV=1 if motor vehicles turned right at a gap acceptance, but 0 if not.
Gap	Gap which is rejected or accepted (sec).
Car, Mc, Rider, Van, Lorry, and Bus.	Car, Mc, Rider, Van, Lorry and Bus=1 if the RMV is car, and 0 if otherwise.
SCar, SMc, SBus, SLorry, SVan	Second vehicle is passenger car, motorcycle, bus, lorry and van passing the RMV on the major road
Gap1,2,3,4,5	If the gap was gap pattern 1,2,3,4,5 in Fig. 4, Gap1,2,3,4 and 5 =1, but 0 if not.
Chlzation	If channelization facility is in unsignalized intersection, so Chlzation = 1, but 0 if not.
AGc	If angular conflict (AGc) detect=1, but 0 if not
REc	If rear-end conflict (REc) detect=1, but 0 if not

Table 1. Attributes of Traffic Behaviour Models

3. Fit Indices

They are the ninth type of model fit and its level of acceptance is summarized in Table 2. The indices include Chi-square, GFI, AGFI, RMSEA, RMSR, SRMR, NFI, CFI, and TLI

3.1 Chi-square

Chi-square value is used to assess the overall model fit. The covariance is fitted in the model when the discrepancy test between sample and the matrices conducts using Chi-square. It is also identified as hard core of fit measure. If the index is at 0.05 level, it shows a not-so-significant value [17,4]. Chi-square or CMIN/df with value of 3 to 5 is considered a good fit index [18,6].

3.2 Goodness-of-fit statistic (GFI)
GFI index has been introduced by [19]. As the alternative test to Chi-square. Its function is to estimate the proportion of the variance by projected covariance of the population. The range for this index between 0 to 1. Typically, small samples and lower factor loading the threshold is 0.95, however GFI 0.90 is widely recommended [20,21].

3.3 Adjusted goodness-of-fit statistic (AGFI)
It is modification from GFI by adjust the degree of freedom. AGFI can be ranging from 0 to 1. Normally the widely recommended threshold is 0.90 [18,19].

3.4 Root mean square error of approximation (RMSEA)
The model advocates parsimony developed by [22]. It reports the best result fit index [18]. proposed that a good model fit should obtain an RMSEA index of 0.7 or less.

3.5 Root mean square residuals (RMSR)
It is calculated by the square root of the mean of the residuals the sample size covariance matrix and the projected covariance model [17]. suggests fitted residuals obtained by comparing the sample covariance matrix and the hypothesized covariance matrix. The closer to 0 or less than 0.5 indicate the better model fit.

3.6 Standardized RMSR (SRMR)
It overcomes the issue faced by RMSR and can be understood properly. SRMR index range lies between 0 to 1. The indices value of 0.5 or less is commonly being applied [18], However, researcher [23]. proposed a value up to 0.08 also might be acceptable in the Model fit.

3.7 Normed fit index (NFI)
Defines this index by comparing the null model or independence model and the chi-square value of the model [25]. Null model shows that all measured variables/parameters are uncorrelated, considering the weakest possible scenario. Therefore, by using NFI improvement can be assessed. A good model fit is when a threshold value of 0.90 and above achieved. The study conducted by [23]. Recommends index above of value 0.95 for small sample size.

3.8 Comparative fit index (CFI)
It is among the favourite indices used in SEM. CFI also compares the model fit with an independent or null model. The significant difference is that it discusses latent factors instant of indicators. Like NFI, a threshold value of 0.90 or (> 0.95 small sample) and above, indicates a good model fit [10].

3.9 Tucker and Lewis Index (TLI)
It is not affected by small sample size. A threshold value of 0.90 an above performs a good model fit. Usually TLI values less than GFI [10,24].

Type	Index	Threshold
Absolute Fit Measures	Chi-square	p-value>0.05
	CMIN/df	<5
	Goodness-of-fit Index (GFI)	> 0.90- 0.95
	Adjusted goodness-of-fit Index (AGFI)	>0.90
	Standardized Root mean square residual	<0.05
	(SRMSR)	<0.08
Incremental Fit Measures	Root mean square error of approximation	
	(RMSEA)	>0.95
		>0.90
	Comparative Fit Index (CFI)	>0.90
	Normed Fit Index (NFI)	
	Turker-Lewis Index (TLI)	

Table 2: Type of Model Fit and Level of Acceptance

4. CB-SEM(Amos)
To confirm the measurable indicator in Exploratory Factor Analysis (EFA), Confirmatory Factor Anylsis (CFA) was implemented and it functions to validate the construct. The EFA output can be visualized and obtained in Model Fit through conducted CFA test. The final structure model considering six latent predictors after CFA is applied with experiatial data. This study emphasizes that CFA justifies the measurement model, menwhile SEM function is to visualize the connecting path analysis of hypotheses between the factors (refer Figure 1). Two stages are applied in single relationship model. In first phase, the observed item loading under the individual construct are visualized. Second phase, the relationships between the four factors are measured.

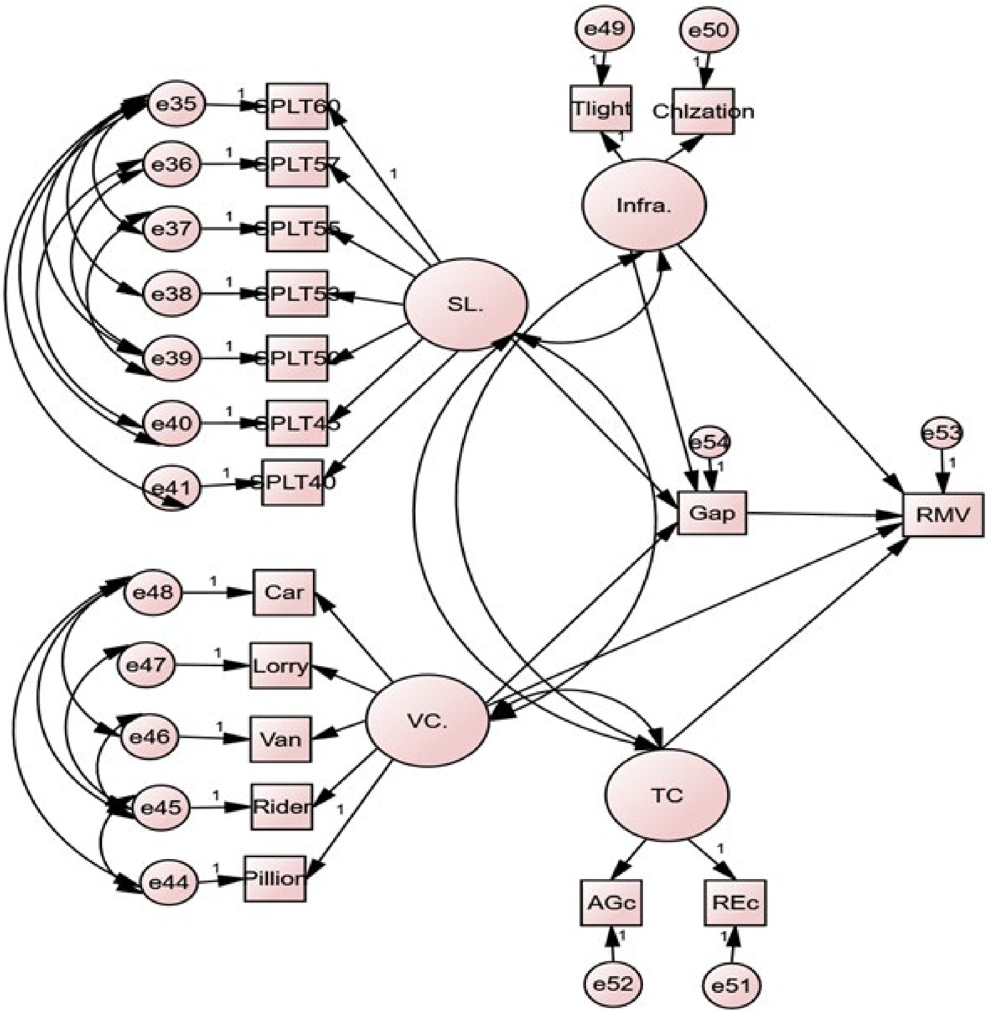

Figure 1: CB-SEM Maximum likelihood Structure Model

4.1 PLS-SEM (Smart PLS) Algorithm and Consistent PLS-SEM Algorithm (Smart PLS)

CB-SEM is based on the covariance concept meanwhile Smart PLS-SEM concept is based on partial least square. The same dataset implemented in CB-SEM and PLS-SEM is to construct the model (refer Figure 5,6). The relationship among the constructs and item loadings against the construct are visualized in the model diagram. In this study, the author has constructed several models before achieving the significance Model Fit. Both approach PLS-SEM and Consistent PLS-SEM were conducted and the study found the similarity in term of result or output in Model Fit for both methods. Previous researcher also prefers to apply consistent PLS algorithm for appropriate structural relationship [26]. Therefore, we decided to make a comparison between Consistent PLSc-SEM algorithm-1 and Consistent PLSc-SEM algorithm-2. The comparison between CB-SEM and PLSc-SEM in term of item loading is quite different (Table -1).

Construct	Variable	PLSc-SEM-1 (Consistent)	PLSc-SEM-2 (Consistent)	CB-SEM
Vehicle Category (VC)	Car	1.90	0.22	2.61
	Lorry	0.78	0.33	-0.18
	Rider	1.42	1.10	2.43
	Pillion	1.05	0.75	1.00
	Van	0.76	0.34	-0.09
Speed Limit (SL)	SPLT40	-0.47	-0.47	0.15
	SPLT45	0.76	0.77	0.52
	SPLT50	0.28	0.28	0.80
	SPLT53	-0.06	-0.06	0.79
	SPLT55	0.04	0.04	-0.84
	SPLT57	0.69	0.70	0.88
	SPLT60	-0.41	-0.41	1.00

Type of Conflict (TC)	AGc REc	- -	-0.49 0.53	0.65 1.00
Infrastructure	Chnlzation Tlight	0.70 0.89	0.70 0.88	-0.12 1.00
Vehicle Gap (VG)	Gap	1.00	1.00	-
Right-Turn Motor Vehicle (RMV)	RTurn	1.00	1.00	-

Table 1: Loading of Variable CB-SEM vs Consistent PLSc-SEM Algorithm

4.2 Relationship Among the Construct

The development and relationship of structural path between the construct is shown in Table 3. They are four and six hypotheses or relationship in the structural equation modelling using consistent PLS-SEM Algorithm-1 and PLSc-SEM Algorithm-2 respectively. In PLS-SEM Algorithm-1 infrastructure (Infra), speed limit (SL), vehicle category (VC) has great impact on vehicle gap (VGap) at 95%, 99% and 99% confident level respectively. Consequently, vehicle gap has effect on right turn-motor vehicle (RMV) at 99% confident level. In PLS-SEM Algorithm-2, infrastructure and speed limit has a great impact on vehicle gap (VGap) at 99% confident level. Meanwhile vehicle gap (VGap), vehicle category (VC) and type of conflict (TC) have significance influence on right-turn motor vehicle (RMV) achieved 99% confident level, accept type of conflict received 95% confident level. Consequently, vehicle category (VC) was found to be having significant effect on type of conflict (TC) at 99% confident level. In CB-SEM, only two construct paths have been identified to have similarity in PLSc-SEM Algorithm. They are types of conflict and vehicle gap which have influenced the RMV at 99% significant level.

CB-SEM (Amos) to confirms the measurable indicator in Exploratory Factor Analysis (EFA), Confirmatory Factor Anylsis (CFA) was implemented and it functions to validate the construct. The EFA output can be visualized and obtained in Model Fit through conducted CFA test. The final structure model considering four latent predictors, after CFA is applied with experiatial data. This study emphasizes that CFA justifies the measurement model, menwhile SEM function visualizes the connecting path analysis of hypotheses between the factors (refer Figure 1). Two stages are applied in single relationship model. In first phase, the observed item loading under the individual construct is visualized. Second phase, the relationships between the four factors are measured.

Relationship/Hypotheses	PLSc-SEM-1	PLSc-SEM-2	CB-SEM
Infra -> VGap	0.19*	0.26**	0.35**
Speed Limit -> VGap	0.71**	0.71**	0.53
Type of Conflict -> RMV	-	0.08*	9.19
VGap -> RMV	0.31**	0.32**	0.08**
Vehicle Category -> RMV	-	0.14**	0.03
Vehicle Category -> Type of Conflict	-	0.61**	-
Vehicle Category -> VGap	0.17**	-	0.64

*Significant at 5%, ** significant at 1%

Table 3: Hypotheses Among Construct Path Consistent PLS-SEM Algorithm and CB-SEM

4.3 Consistent PLS-SEM Algorithm

In this section, the authors select consistent PLS-SEM Algorithm-2 rather than PLS-SEM Algorithm 1, to determine the path coefficient, associated t-stat, p-value and direct connection between variables. The reason is that PLSc-SEM-2 has included appropriate items loading, construct path as well as model fit which will be discussed in the next section. This study has 18 direct relationships and out of 18 hypotheses only 4 are insignificance in the model. Table 4, shown Hypotheses H1, H2, H5, H6, H7, H8, H9, H10, H11, H12, H13, H14, H15, H16, and H17 achived significance level at 99% except for H3, H4, H8 and H18 was found disqualified in the model. This shows that from infrastructure group, only channelization was rejected, meanwhile trafffic light was accepted. Consequently, in vehicle category group, only van was rejected and the others were accepted (lorry, car, rider and pillion). In group speed limit (SL) and traffic conflict (TC) all the variables were found effectively significant on RMV. This study reveals that the similarity is in consistent PLSc-SEM Algorithm and PLS-SEM Algorithm in term of output result such as loading of variables, tested hyphothese and construct path. Although the R-square obtained in the model was 0.424, almost relationship between variables was found significant. The final network diagram adopting PLSc-SEM Algorithms-1 and 2 is illustrated in Figure 4 and Figure 5 respectively. The Smart-PLSc has advantage on the overall view of dataset in the model.

	Relationship/Hypotheses	Beta	T-Stat	P values
H1	AGc <- Type of Conflict	-0.985	5.473	0.000
H2	Car -> Vehicle Category	-0.663	13.355	0.000
H3	Chalization -> Infra	0.317	1.417	0.156
H4	Gap <- VGap	1.000	-	-
H5	Lorry -> Vehicle Category	-0.103	3.269	0.001
H6	Pillion -> Vehicle Category	0.141	2.756	0.006
H7	REc <- Type of Conflict	0.987	5.476	0.000
H8	RTurn <- RMV	1.000	-	-
H9	Rider -> Vehicle Category	0.925	43.847	0.000
H10	SPLT40 -> Speed Limit	0.309	5.187	0.000
H11	SPLT45 -> Speed Limit	0.885	14.461	0.000
H12	SPLT50 -> Speed Limit	0.870	14.572	0.000
H13	SPLT53 -> Speed Limit	0.813	11.351	0.000
H14	SPLT55 -> Speed Limit	-0.789	8.546	0.000
H15	SPLT57 -> Speed Limit	0.781	8.377	0.000
H16	SPLT60 -> Speed Limit	0.625	5.516	0.000
H17	Tlight -> Infra	0.859	5.403	0.000
H18	Van -> Vehicle Category	-0.069	1.626	0.104

Table 4: Tested Hypotheses PLSc-SEM Algorithm-2 Model

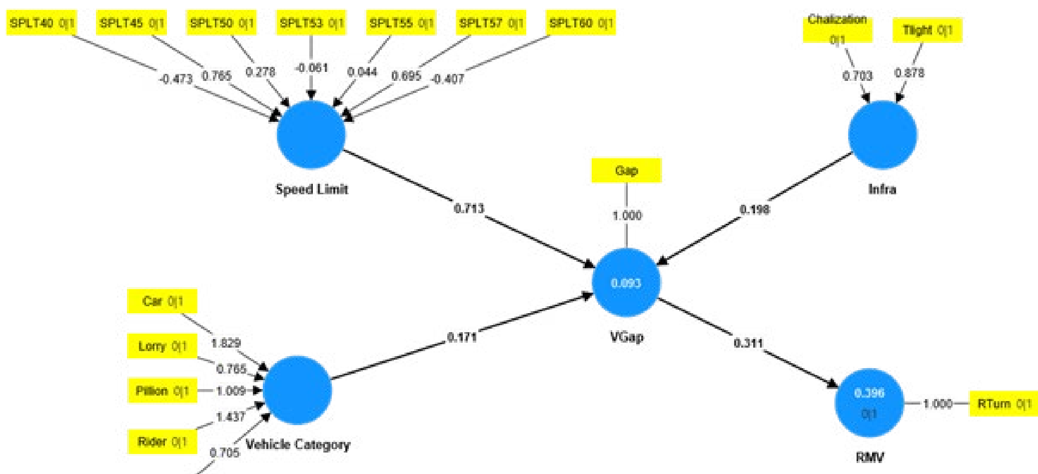

Figure 2: SEM (Consistent PLS Algorithm-1).

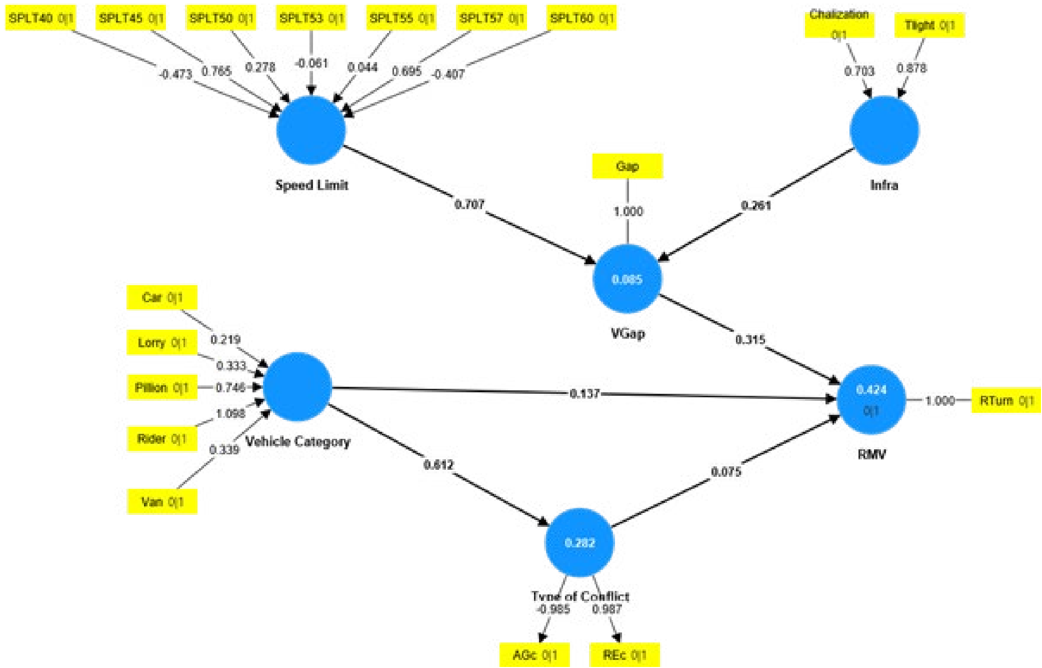

Figure 3: SEM (Consistent PLS Algorithm-2)

4.4 Model Fit Indices

In CB-SEM, the network analysis was implemented in structural model that must be justified or tested for model fit. There are more than 10 fitness measures to test and compare the result of LISREL [27]. Although these measures are applicable in CB-SEM, they are not totally useful in adequately evaluating model fit in PLS. The deficiency aspect as concept develop behind PLS-SEM is different from CB-SEM, thus need appropriate measurement to assess the model fit. In PLS-SEM literature is remind considering this aspect and it is carefully not to present model fit indices to summarize the finding [21]. CB-SEM is designed for theory testing that requires precise model fit assessment to measure and validate the indices.

As mentioned in the previous section, model fit indices in CB have many selections as compared to PLS provide less option. Several estimated measure like Chi2, NFI, and SRMR are available in PLS. Furthermore, measure like the square Euclidean distance (d_ULS) and the Geodesic distance (d_G) are also provided by PLS [28]. In this study, almost all the good of fit (GoF) indices comply the threshold level require from the previous research works (refer Table-5). AGFI for CB-SEM is a bit lower than the set level (0.89). However, GFI looks good (0.92), and NFI is achieved (0.92), CFI stated (0.94) are above the benchmarks. RMSEA is at 0.03 a smaller than the standard required. In this study, consistent PLS-SEM algorithm -1, consistent PLS-SEM algorithm 2 and CB-SEM has recorded SRMR at 0.05, 0.06 and 0.02 respectively, indicating a better model fit. Both PLSc-SEM-1 and PLSc-SEM-2 reported NFI (0.95) and (0.94) respectively, higher than threshold. Meanwhile, square Euclidean distance (d_ULS) and the Geodesic distance (d_G) represent value that are insignificant, explaining a good model fit (for both consistent PLS-SEM) [21].

Previous researchers have suggested PLS-SEM to provide estimated model values like in CB-SEM, however other studies argue the clarity to select all variety of estimated model values [7]. Since PLS method focusing on estimated Model, the indices use in PLS-SEM, would be adequate to assess the model fit. Implementing CB-SEM is quite challenging and exhausting because the system has different approach on the GoF, including both the model fitness and the predictors in the model. To have better point of view, using PLS might have advantage to include overall dataset in the network diagram and using Model fit indices to validate the model.

	PLSc-SEM Algorithm-1	PLSc-SEM Algorithm-2	CB-SEM
Chi-square	-	-	507.29
GFI	-	-	0.92
AGFI	-	-	0.88
NFI	0.95	0.94	0.92
CFI	-	-	0.94
TLI	-	-	0.90
RMSEA	-	-	0.03
SRMR/RMR	0.05	0.06	0.02
d_ULS	0.68	0.60	-
d_G	0.13	0.15	-

Table 5: Model Fit Consistent PLSc-SEM and CB-SEM

Root mean squared error of approximation calculation formula for CB-SEM model is defined by Equation 1.

$$RMSEA = \sqrt{\frac{(\chi 2 - df_{CB})}{df_{CB}(n-1)}} \quad (1)$$

Where n number of observations for all models was (841), df_{CB} the degrees of freedom in model (111) and Chi-square χ^2 of the CB-SEM Model, were (686).

5. Discussion

As mentioned before, CB-SEM and PLS-SEM have different approach and concept in the development of the program. Whereas CB-SEM emphasizes the covariance concept, theoretical, and involved complex fit indices meanwhile the PLS-SEM does the model estimate, latent factor, construct path, and adequate fit indices. In term of application, PLS-SEM has more option, flexible and fast to construct the network model as compared to CB-SEM which has a bit constraint to develop the network and need a frequent attempt to determine the model fit even it has a modification index (MI).

This study would like to summarize the vision from this article in three different approaches: theory construct, theory application and comparison of composite models. Some suggestion can be applied for future research as follow in this domain. First, the composite-based models should verify with both methods to test the efficacies. The potential SEM will become more composite-based models rather factor-based [29]. Second, more consequents and antecedents' variables with few adjust parameter can be discovered. Finally, specific traffic characteristic domains can be used and a comparative evaluation can be carried out.

6. Conclusion

We can see those composite models and multiple regression models analysed simultaneously with observe and un-observed effects among latent variables are simply described by SEM. Understanding the logic and concept behind the SEM is the most critical. CB-SEM is more of a confirmatory study than exploratory, thus fundamental theory are crucial. First, begin with model specification. Then, model estimation and finally model validated with statistical tools. Typically, the measurement model and the path model are used to analyse how close the observe values are estimated. The degree of impact on the dependent construct and the conceptual model depends on path coefficient.

Finally, the overall study can conclude that all the model fit indices must significance (Absolute and Incremental), after the measurement is validate, the final structural path model is completed. This study found that by using same dataset, PLS and PLSc initiate similar results, meanwhile PLSc-1 and PLSc-2 have a close output. Furthermore CB-SEM item-loading is higher than PLSc. There is no single way to success. CB or PLS or PLSc do not bother. To understand the underlying theories is critical for selecting the method. Composite-models should use PLSc, whereas factor-based models would opt for CB.

Acknowledgements

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References

1. Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Cham: Springer International Publishing.
2. Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis, 1*(2), 107-123.
3. Haenlein, M., & Kaplan, A. M. (2004). A beginner's guide to partial least squares analysis. *Understanding statistics, 3*(4), 283-297.
4. Hooper, D., Coughlan, J., Mullen, M. R., Mullen, J., Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: guidelines for determining model fit structural equation modelling: guidelines for determining model fit. Dublin Institute of Technology ARROW@ DIT, 6 (1), 53–60.
5. AlNuaimi, B. K., Khan, M., & Ajmal, M. M. (2021). The role of big data analytics capabilities in greening e-procurement: A higher order PLS-SEM analysis. *Technological Forecasting and Social Change, 169,* 120808.
6. Mueller, R. O., & Hancock, G. R. (2018). Structural

equation modeling. In *The reviewer's guide to quantitative methods in the social sciences* (pp. 445-456). Routledge.. 46 (1), 163–177.

7. Hayes, A. F., Montoya, A. K., & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. *Australasian Marketing Journal, 25*(1), 76-81.
8. Ullman, J. B., & Bentler, P. M. (2012). Structural equation modeling. *Handbook of Psychology, Second Edition, 2*.
9. Hair Jr, J.F., Howard, M.C., Nitzl, C., 2020. Assessing measurement model quality in PLSSEM using confirmatorycomposite analysis. *J. Bus. Res. 109,* 101–110.
10. Malhotra, N. K., Kim, S. S., & Patil, A. (2006). Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research. *Managementscience, 52*(12),1865-1883..
11. Mustakim, F., Ahmad, M. N., Kadir, R. A., Sulaiman, R., Ahmad, A., Aziz, A. A. D., & Mahmud, A. (2023). Ontologies for Supporting Traffic Behaviour, Critical Gap, and Conflict Models at Unsignalized Intersection Routes. *Journal of Humanities & Social Sciences, 6*(7), 195-213.
12. Mustakim, F., Aziz, A. A., Siong, L. H., Bakhuraisa, Y., & Rahman, N. Z. B. A. (2024). Impact of Traffic Characteristic at Unsignalized Intersection in Mixed Traffic Condition using Logistic Regression Method (LRM) and Artificial Neural Network (ANN). *J Sen Net Data Comm, 4*(2), 01-15.
13. Mustakim, F., Aziz, A. A., Siong, L. H., Bakhuraisa, Y., & Rahman, N. Z. B. A. (2024). Impact of Traffic Characteristic at Unsignalized Intersection in Mixed Traffic Condition using Logistic Regression Method (LRM) and Artificial Neural Network (ANN). *J Sen Net Data Comm, 4*(2), 01-15.
14. Mustakim, F., Aziz, A. A., Mahmud, A., Jamian, S., Hamzah, N. A. A., & Aziz, N. H. B. A. (2023). Structural Equation Modeling of Right-Turn Motorists at Unsignalized Intersections: Road Safety Perspectives. *International Journal of Technology, 14*(6).
15. Fajaruddin, M., Fujita, M., & Wisetjindawat, W. (2013). Analysis of Fatal-Serious Accidents and Dangerous Vehicle Movements at Access Points on Malaysian Rural Federal Roads. *Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management), 69*(4), 286-299.
16. Kline, R. B. (2023). *Principles and practice of structural equation modeling.* Guilford publications.
17. Shi, D., & Maydeu-Olivares, A. (2020). The effect of estimation methods on SEM fit indices. *Educational and psychological measurement, 80*(3), 421-445.
18. Jöreskog, K. G., & Sörbom, D. (1993). *LISREL 8: Structural equation modeling with the SIMPLIS command language*. Scientific software international.
19. Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of MultivariateDataAnalysis, 1*(2),107-123.
20. Miles, J., & Shevlin, M. (2007). A time and a place for incremental fit indices. *Personality and individual differences, 42*(5), 869-874.
21. Sebold, M., Schad, D. J., Nebe, S., Garbusow, M., Jünger, E., Kroemer, N. B., ... & Huys, Q. J. (2016). Don't think, just feel the music: Individuals with strong Pavlovian-to-instrumental transfer effects rely less on model-based reinforcement learning. *Journal of cognitive neuroscience, 28*(7), 985-995.
22. Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal, 6*(1), 1-55.
23. Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological bulletin, 88*(3), 588.
24. Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological bulletin, 107*(2), 238.
25. Shmueli, G., Ray, S., Estrada, J. M. V., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of business Research, 69*(10), 4552-4564.
26. Lohmöller, J. B. (2013). *Latent variable path modeling with partial least squares.* Springer Science & Business Media.
27. Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational statistics & data analysis, 81*, 10-23.
28. Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies!. *Journal of business research, 69*(10), 3998-4010.