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ANALYSIS OF KNOWLEDGE OF MOTOR VEHICLE DRIVERS ON TRAFFIC SIGNS AND CONGESTION IN EDUCATIONAL ENVIRONMENTS

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Abstract

Transportation is done by humans to meet their needs. Safe and smooth transportation requires traffic signs. Transportation within the Universitas Brawijaya (UB) campus is not smooth due to roadside parking activities, parking exits, and entry activities, vehicle turning activities, and incomplete signs. This study aims to model congestion in the UB campus environment and related office work by using the Partial Least Square (PLS)-path modeling approach. Respondents in this study consisted of 35 lecturers, 35 education staff, and 35 students. The results show that there is a significant negative effect between driver behavior (X1=-0.43) on Congestion (Y1) and a significant positive effect between Congestion (Y1=0.34) and working conditions/employee performance (Y2). And there is a significant influence between Driver Behavior (X1 = -0.147) on employee performance (Y2) indirectly through the Congestion variable (Y1). The overall model test results show good results (meeting the Goodness of Fit Indices limits) meaning that the data support the theoretical model developed. Recommendation or not to continue that Universitas Brawijaya needs to increase the parking area, complete traffic signs and improve driving behavior with discipline.

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INTRODUCTION

Transportation is an activity that is always carried out by humans every day to meet their needs. In carrying out transportation, traffic signs are needed to support smooth and safe traffic (Manan et al., 2018). Transportation within the campus of Universitas Brawijaya (UB) is not smooth and has the potential to experience congestion due to roadside parking activities, parking entry and exit activities, vehicle turning activities, incomplete signs, and the presence of online motorcycle taxis. The existence of this activity contributes to congestion on the UB campus. In addition, the limited parking space in UB and the dense traffic in UB, and the inadequate road width due to the use of roadside parking also contribute to congestion. The capacity of car parking in UB is 624 SRP, while the motorcycle capacity is 5,312 SRP. The need for car parking space is 693 SRP, and the need for motorcycle parking space is 5,902 SRP (Wahyunita, 2015).

On the other hand, the knowledge of road users in UB about signs is not sufficient. Direction signs and large maps of directions are also not available at the main gate of UB, which causes guests or people who have just arrived at UB to find their destination difficult. This situation needs to be considered and examined carefully to produce policies that are comprehensively beneficial to all UB academics. Traffic jams will allow various environmental impacts to arise, both the community environment and the business environment (Istiyanto, 2019; Sholihah et al., 2020). In addition, congestion has an impact on high Vehicle Operating Costs (BOK). The high BOK will affect the performance of public transport companies (Herdiani et al., 2021). In this case, the research is limited to the office environment related to employee performance. The resulting congestion resolution must have a positive impact on the office environment.

This study aims to model congestion on the UB campus and its impact on the office environment using the Partial Least Square-path modeling approach. It is expected that both the direct and indirect effects of the factors that cause congestion and their impact on the environment can be evaluated inferentially.

METHODS

Statistical modeling that involves relationships between variables, as well as indicator models, simultaneously is called structural equation modeling (SEM) (Solimun et al., 2017). SEM analysis as a representation of the system under study should be able to explain the behavior of the system close to real conditions. Statistical modeling in this case uses the PLS approach. According to Abdillah and Hartono (2015), PLS is a variant-based SEM statistical method designed to solve multiple regression when experiencing specific problems with data, such as small sample size, missing data, and multicollinearity. The PLS method is a powerful analytical method because it can be applied to all data scales, does not require a lot of assumptions and the sample size does not have to be large (Ghozali, 2008).

PLS was developed by Wold as a general method for estimating path models between latent variable relationships that are indirectly measured by various indicators. PLS can simultaneously test the measurement model (outer model) as well as test the structural model (inner model). The model specification in SEM-PLS consists of a structural model (inner model) which is represented in circles or ovals and describes the relationship between latent variables. Furthermore, the measurement model (outer model) describes the relationship between latent variables and indicator variables in the form of rectangles (Hair et al., 2014).

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RESULTS AND DISCUSSIONS

Outer Model Graph

The outer model is a model that defines how each manifest variable relates to its latent variable. The following is an example of a model path measurement model diagram.

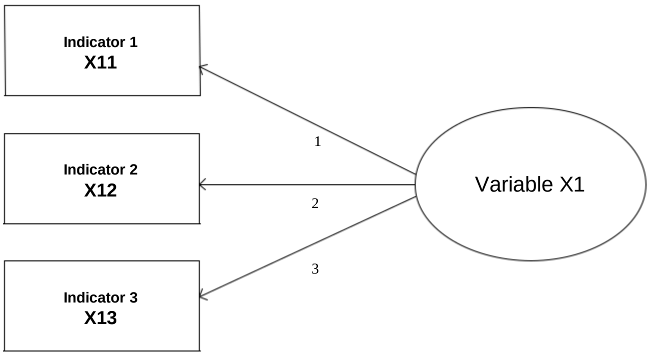

Figure 1. Example of Path Measurement Model Diagram

Based on the Figure 1, the equation can be obtained which shows the measurement model is reflective

$$X_{jk} = \lambda_{ik} X_j + e_k$$

where:

X_{jk} : the k-th indicator of the j-th latent variable X

: outer model coefficient of latent variable X

e_k : error value of the kth outer model variable X

Inner Model Graph

The inner model is a model that predicts causality between latent variables.

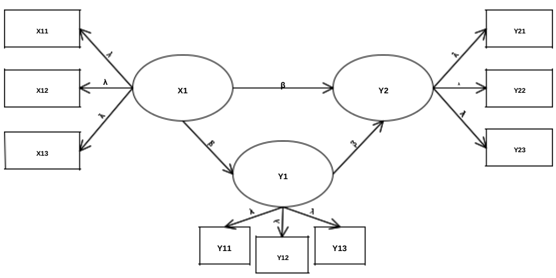

Figure 2. Graph of SEM

Parameter Estimation

The essence of the SEM-PLS procedure is to determine the weights used to estimate these latent variables. According to Solimun (2010), parameter estimation in PLS includes 3 categories. The first category, namely the weight estimate, is used to calculate the value of the latent variable. The second category is the path estimate that links between latent variables (path coefficient) and between latent variables and their manifest variables (loading). The third category relates to means and regression constant values for manifest variables and latent variables. Estimators of component scores for each latent variable are obtained in two ways, namely outside approximation and inside approximation. To obtain the outside approximation weight, the inner model estimator is used, while to obtain the inside approximation weight, the outer model estimator is used. The parameter estimation calculation process is carried out using iterations, the iteration process will stop if convergent conditions have been reached. According to Jaya and Sumertajaya (2008), the way to check convergence at each iteration is with the following criteria.

$$\left|\frac{w_{ki}^{*}-w_{ki}}{w_{ki}}\right| \leq 10^{-5}$$

SEM model with WarpPLS approach

In SEM analysis there are two models, namely the outer model and the inner model. The value of outer loading (for reflexive indicators) and outer weight (for formative indicators) shows the weight of each indicator as a measure of each latent variable. The indicator with the largest outer loading or outer weight indicates that the indicator is the strongest (dominant) variable measurer.

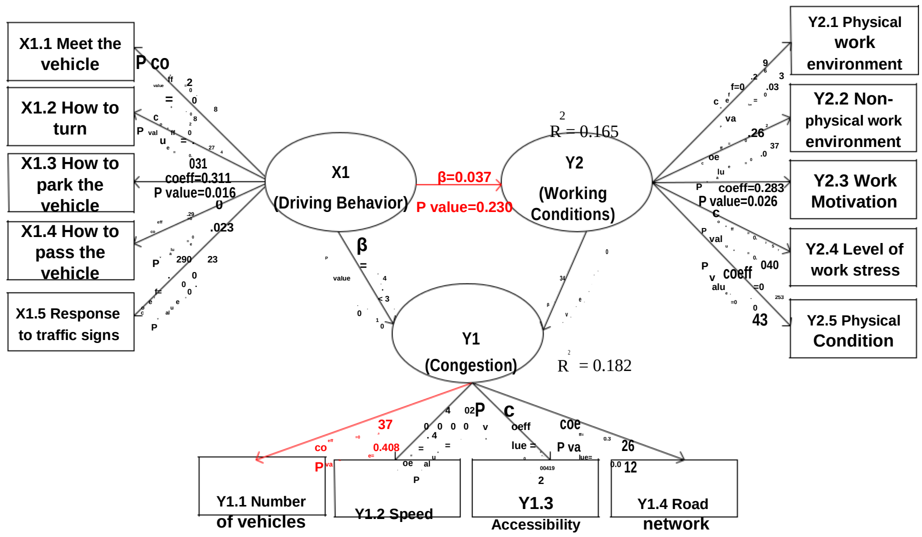

Figure 3. Graph of SEM Model with WarpPLS Approach

Testing the Variable Model (Outer Model)

- **Driving Behavior Variables**

The Driving Behavior Variable is measured using a reflective indicator model, so it is necessary to pay attention to the outer loading value to determine the strong and weak influence of each indicator on the Driving Behavior Variable. The variable consists of five indicators. The following table and figure present the results of outer loading on the indicators of the Driving Behavior Variable (X1).

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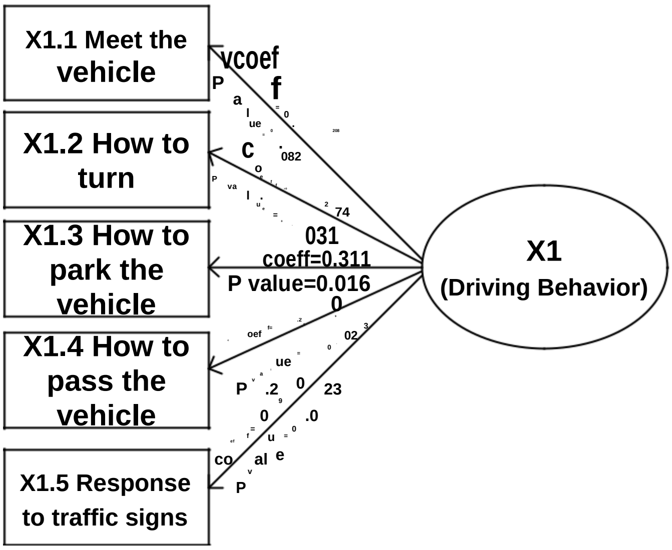

Figure 4. The Results of Outer Loading on The Indicators of The Driving Behavior Variable

Table 1. Driving Behavior Variable Measurement Model (X1)

Variable	Indicator	Indicator Models	Outer Loading	P Value	Information
Driving Behavior (X1)	Met the vehicle (X1.1)	reflective	0.208	0.082	Significant
	How to turn (X1.2)	reflective	0.274	0.031	Significant
	How to park the vehicle (X1.3)	reflective	0.311	0.016	Significant
	How to pass the vehicle (X1.4)	reflective	0.290	0.023	Significant
	Response to traffic sign (X1.5)	reflective	0.291	0.023	Significant

From Table 3, it can be concluded that the five indicators above are significant as a measure of the Driving Behavior Variable (X1).

(Congestion Variable Y1)

The Congestion Variable is measured using a reflective indicator model so it is necessary to pay attention to the outer loading value to determine the strong and weak influence of each indicator on the congestion Variable. The variable consists of four indicators. The following table and figure present the results of outer loading on the indicators of the Congestion Variable (Y1). The following table and figure present the results of outer loading on the indicators of the congestion variable (Y1).

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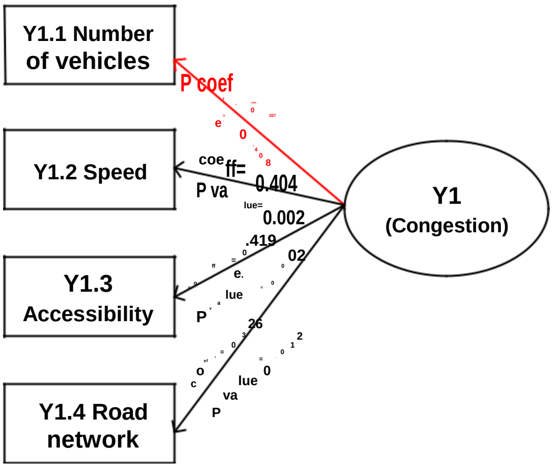

Figure 5. The Results of Outer Loading on The Indicators of The Congestion Variable

Table 2. Congestion Variable Measurement Model (Y1)

Variable	Indicator	Indicator Models	Outer Loading	P Value	Information
Congestion (Y1)	Number of vehicles (Y1.1)	reflective	0.037	0.408	Not significant
	Speed (Y1.2)	reflective	0.404	0.002	Significant
	Accessibility (Y1.3)	reflective	0.419	0.002	Significant
	Road network (Y1.4)	reflective	0.326	0.012	Significant

From Table 2, it can be concluded that there is one variable, namely, the number of vehicles is not significant as a measure of the congestion variable, and the other three indicators are significant as a measure of the Congestion Variable (Y1).

Working Conditions Variable (Y2)

The Working Conditions Variable is measured using a reflective indicator model, so it is necessary to pay attention to the outer loading value to determine the strong and weak influence of each indicator on the Working Conditions Variable. The variable consists of five indicators. The following table and figure present the results of outer loading on the indicators of the Working Conditions Variable (Y2). The following table and figure present the results of outer loading on the indicators of the Working Conditions Variable (Y2).

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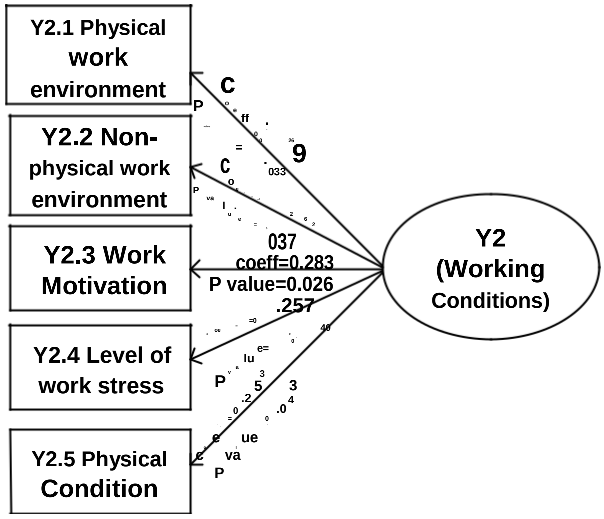

Figure 6. The Results of Outer Loading on The Indicators of The Working Conditions Variable

Table 3. Working Condition Variable Measurement Model (Y2)

Variable	Indicator	Indicator Models	Outer Loading	P Value	Information
Working Conditions (Y2)	Physical work environment (Y2.1)	reflective	0.269	0.033	Significant
	Non-physical work environment (Y2.2)	reflective	0.262	0.037	Significant
	Work motivation (Y2.3)	reflective	0.283	0.026	Significant
	Level of work stress (Y2.4)	reflective	0.257	0.040	Significant
	Physical condition (Y2.5)	reflective	0.253	0.043	Significant

From Table 3, it can be concluded that the five indicators above are significant as a measure of Working Conditions (Y2).

Testing the Hypothesis Model (Inner Model)

Structural model testing (structural model) tests the hypothesis in research. Hypothesis testing is done by t test (t-statistic) on each path of partial direct influence. The second part of the SEM analysis is the interpretation of the structural model or structural model. The structural model presents the relationship between research variables. The structural model coefficients state the magnitude of the relationship between one variable and another. There is a significant influence between one variable on another variable if the P-value <0.1.

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Table 4. Direct Influence

Variable		Path Coefficient	P-values	Conclusion
Predictor	Response			
Driving Behavior (X1)	Congestion (Y1)	-0.43	<0.1	Significant
Driving Behavior (X1)	Working Conditions (Y2)	-0.11	0.23	Not significant
Congestion (Y1)	Working Conditions (Y2)	0.34	<0.1	Significant

Graphically the results of hypothesis testing in the SEM structural model of the WarpPLS approach can be seen in the Figure 7, where graphically presented as follows (the red line shows a non-significant effect, and the black line shows a significant effect).

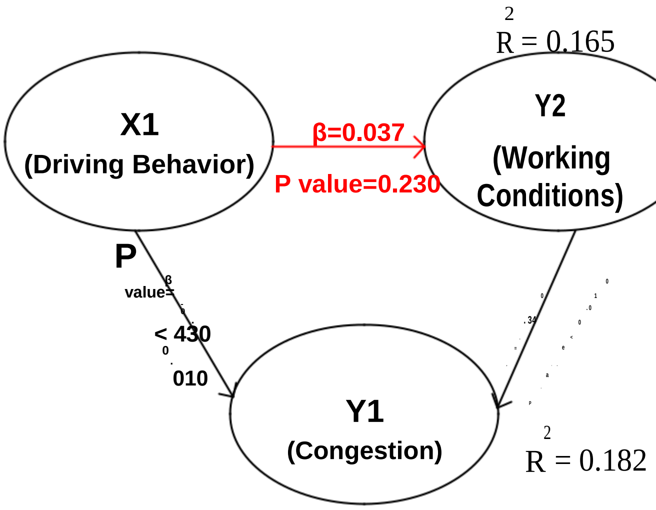

Figure 7. The Results of Hypothesis Testing in The SEM Structural Model of The Warppls Approach

Table 5. Indirect Influence

Variable			Path Coefficient	P-Value	Conclusion
predictor	Mediation	Response			
Driving Behavior (X1)	Congestion (Y1)	Working Conditions (Y2)	-0.147	0.088	Significant

The effect of driving behavior (X1) on working conditions (Y2) through the variable traffic jam, the path coefficient is -0.147 and the P-value is 0.088. Because the P-value <0.1 indicates that there is a significant influence between Driving Behavior (X1) on Working Conditions (Y2) indirectly through the variable Congestion (Y1).

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Table 6. Coefficient of Determination

Response Variable	R-squared
Y1	0.182
Y2	0.165
Total	0.347

The calculation results produce a coefficient of determination of 0.347 or 34.7%. The coefficient of determination of 34.7% also indicates that the diversity of data that can be explained by the model is 34.7% or in other words, the information contained in the data is 34.7%. can be explained by the model. While the rest is explained by other variables (which are not included in the model) and errors. Thus the structural model that has been formed is not appropriate.

Table 7. Model Feasibility Test Results

No	Model Fit/Quality Index	Mark	Criteria	Information
1	Average path coefficient	APC = 0.294P = 0.011	Significant if $P < 0.05$	Significant
2	Average R-squared	ARS = 0.174P = 0.062	Significant if $P < 0.05$	Not significant
3	Average adjusted R-squared	AARS = 0.140P = 0.090	Significant if $P < 0.05$	Not significant
4	Average Block VIF	AVIF = 1.251	*acceptable* if AVIF ≤ 5 ideal if AVIF ≤ 3.3	Ideal
5	Average full collinearity VIF	AFVIF = 1.199	*Acceptable* if AFVIF ≤ 5 ideal if AFVIF ≤ 3.3	Ideal
6	Tenenhaus GoF	GoF = 0.309	small if GoF ≥ 0.1 medium if GoF ≥ 0.25 large if GoF ≥ 0.36	Medium
7	Sympson's paradox ratio	SPR = 1,000	*acceptable* if SPR ≥ 0.7 ideal if SPR = 1	Ideal
8	R-squared contribution ratio	RSCR = 1,000	*acceptable* if RSCR ≥ 0.9 ideal RSCR = 1	Ideal
9	Statistical suppression ratio	SSR = 1,000	*acceptable* if SSR ≥ 0.7	*Acceptable*
10	Nonlinear bivariate causality direction ratio	NLBDR = 0.833	*acceptable* if NLBCDR $\geq$ 0.7	*Acceptable*

The Table 7 represents a summary of the results obtained in the analysis and recommended values to measure the feasibility of the model.

CONCLUSION

Based on the results of the overall model feasibility test, there are two criteria (Average R-squared and Average adjusted R-squared) that have not reached the expected value limit, while eight other criteria have reached the expected value limits or have met the recommended critical limits of Goodness of fit indices. So it can be concluded that the results of this modeling are acceptable or

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feasible to analyze. It can also be stated that this test produces good confirmation of the variables and the causal relationship between variables. Thus the overall model test results show good results, meaning that empirical data (field data) has supported the theoretical model that was developed.

COMPETING INTERESTS

The authors have no competing interests to declare.

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