THE MODELS OF ACCIDENT SIZE COMPARISONS BETWEEN INTERCITY MOTORWAY ROUTES

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Abstract

Intercity motorways in Thailand play an important role in national development, as they link various industrial zones and main harbors for transporting goods abroad. Furthermore, they connect national tourist attractions. When considering the trend of accident occurrences on motorways, it has been found that the severity of accident trend has leaned forwards to be on the continuous increase. This research attempts to establish guidelines for reducing the severity of accidents on motorways number 7 and number 9 in Thailand; thus, the differences between the two motorways were considered. This research used and analyzed data from 2010 to 2016 from the Intercity Motorway Division, Department of Highways. As the severity of injuries cannot be directly measured, the number of minor injuries, serious injuries, and deaths, as well as the number of vehicles involved in each accident, were chosen for analysis using structural equation modeling (SEM). Subsequently, a multiple group analysis was used to analyze the differences between the two models. The results of the factor analysis revealed significantly different severities of injuries. For motorway number 7, the traffic flow factor mostly affected accident size, followed by the road factor and the environmental factor, respectively. For motorway number 9, only surrounding and road factors affected accident size.

Keywords: Intercity motorway, accident size, structural equation modeling, measurement invariance, Thailand

Introduction

Background

The roads in Thailand, consisting of highways, rural highways, and expressways, are the responsibility of the Ministry of Communication. Based on the number of accidents in 2014, highways had the highest number of accidents (86.31%), followed by rural highways (8.08%) and expressways (5.6%), respectively (Office of transport and traffic policy and planing, 2014). Moreover, when concentrating only the roads controlled by the Department of Highways, which are the greatest number of routes and have relatively high traffic quantity per day when compared to the roads nationwide, it was found that, in 2015, accident occurrences on highways, divided into 18 highway offices throughout the country, had a total of 13,065 accidents with fatalities and injuries (2,118 and 11,750, respectively). For intercity motorways, 510 accidents caused 18

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fatalities and 198 injuries. In a 100-km ratio, the intercity motorway route had the highest proportion of 245.76 accidents with 8.67 fatalities and 95 injuries (Thailand Department of Highway, 2018). Intercity motorways, (i.e., routes with full control of access) are designed for vehicles using higher speeds than usual and paying tolls. At present, the available intercity motorways are motorway number 7 linking roads from Bangkok to Chonburi Province, and motorway number 9 that connects the eastern outer ring roads in Bangkok and Bang Pa-in, Ayudthaya with Bang Phli, Samutprakarn Province. The significance of the two motorways is that they constitute the main routes joining industrial zones in Ayudthaya, Chonburi, and Rayong, as well as multimodal transportation, from roads, to surface transportation, to export goods abroad (Thailand Department of Highway, 2017).

Regarding freight transportation vehicle-kilometers on highways in 2018 (Table 1), intercity motorways accounted for 4% of activity among highway types. However, in terms of freight vehicles, intercity motorways had the most vehicles (about 70%).

Thus, understanding the aspect of crash size among various factors on intercity motorways, policymakers could apply this result to new policies to reduce the accident size, which is one method of sustainable freight transportation development.

Concerning expressways, Ji *et al.* (2014) have identified that expressways have played an important role in national economic development and also resulted in the change of land cover. Zhao *et al*. (2014) have studied characteristic parameters, such as traffic volume, average travel speed, and the density of toll use, which affected the flow speed on expressways, bottlenecks occurring on the ramp of expressways (Sun *et al*., 2015), and the effect of towing on road traffic flow (Han *et al*., 2016). For the study of accidents occurring on expressways, scholars have conducted studies on factors affecting the accident rate on expressways in Korea (Lee and Jeong, 2016), on the relationship between traffic congestion and crashes on urban expressway state roads in central Florida in the United States, (Shi *et al*., 2016) and on expressways in Shanghai, China (Sun *et al*., 2016). Furthermore, researchers have carried out studies on the average speed factor and traffic quantity affecting crash risks (Yu *et al*., 2016) and the prediction of the crash frequency on expressways in China (Ma *et al*., 2017). In Thailand, Rudjanakanoknad *et al*. (2012) conducted a study on expressways analyzing the speed used on Bangkok expressways based on drivers' attitudes. Regarding studies about accident occurrences on expressways, scholars have investigated the effect of injury level occurring on Bangkok expressways and the prediction of loss values by crashes (Ratanavaraha and Suangka, 2014). The Thairoads (2014) has studied the relationship between and predictions about driving speeds and accidents on expressways and motorways in Thailand. The foundation's study was conducted by comparing the vehicles running at speeds that fell in the 85 percentile and the 15 percentile, if the speed difference is low, it will cause fewer fatalities and injuries.

The difference between the two motorways is their purposes. Motorway number 7 was built to develop a transportation route to the eastern coast to solve the congestion problem on Sukhumvit Road, and number 9 serves to decrease the blocking of roads in Bangkok and the metropolitan area, and also be a bypass road reducing the traffic jam in Bangkok and the metropolitan area. Thus, the traffic on motorway number 9 will be higher than that on motorway number 7, and the population around the motorway number 9 area will be also higher. Figure 1(a) shows that motorway number 9 has more traffic, with a maximum range of 57,652-93,287 vehicles per day. Figure 1(b) shows the population living around the two motorways divided by subdistrict. It was found that subdistricts around motorway number 9 had a higher population than those around motorway

Table 1. Freight transportation Vehicle-Kilometers on Highways in 2018

Vehicle – Type (Unit)	Nation Highways			Inter – city Highways	Total
	Primary	Secondary	Provincial		
Freight transportation Vehicle-Kilometers on Highways display on table in 2018 (VK)	33,365,484,829	28,504,951,282	36,267,032,249	3,845,700,553	101,983,168,913
Percentage of Vehicle-Kilometers	33%	28%	36%	4%	100%
Distance	7,527	11,352	32,755	208	51,842
Total freight vehicles (Vehicles)	4,432,773	2,511,007	1,107,221	18,488,944.97	26,539,947
Percentage of freight vehicles%	17%	9%	4%	70%	100%

Note: VK = Vehicle-Kilometer

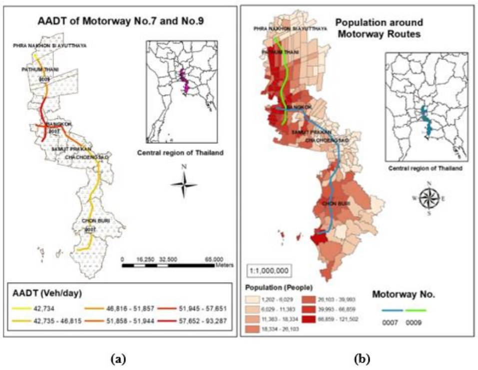

Figure 1. AADT and Population of Motorway routes

number 7. These issues cause different levels of accident severities on the two motorways.

Accident size

The indicators of most accidents are 1) accident frequency, and researchers have studied prediction of different injury levels (Wang *et al.*, 2011); the prediction of crash frequencies classified by crash types (Jonathan *et al.*, 2016); and the prediction of crash frequencies on expressways (Ma *et al.*, 2017). 2) Other researchers have investigated the risk of accidents occurring, including the prediction of crash risks in relation to bus drivers' behaviors (Mallia *et al.*, 2015) and accident risks on expressways in Shanghai (Yu *et al.*, 2016) and in Korea (Kwak and Kho, 2016). 3) Research has also been conducted on accident severity, which is mostly measured by victims' injury levels. There have been many studies on highway accident severity, the model construction of victims' injury levels (Yamamoto *et al.*, 2008), and accident severity levels caused by single-vehicle crashes in Hong Kong (Yau, 2004). Further studies have explored the construction of severity predictions for each injury level on roads in Spain (Carmen Carnero and José Pedregal, 2010), injury levels of rear-end crashes among trucks on roads in Beijing (Yuan *et al.*, 2017), and the factors affecting injury levels (i.e., no injuries, minor injuries, serious injuries, and fatalities in multiple-vehicle crashes) (Bogue *et al.*, 2017).

From the previously reviewed literature, it is evident that there have been many indicators that researchers could not directly measure, so the different indicators need to be collected to additionally cover the causes of accidents. Lee *et al.* (2008) gathered the accident occurrence indicators using the phrase "accident size" for a Korean highway study. The four factors that indicated accident size were the number of deaths, injured people, vehicles involved, and damaged vehicles.

Variable Selections

If the number or the severity of accidents is to be reduced, the factors affecting their causes at different levels should be studied. In the past, scholars have carried out many studies on the factors that potentially cause accidents without considering drivers' demographic data, such as sex and age, as those elements were difficult to control for (Lee *et al.*, 2008). The relevant factors could be divided into three groups.

1) The environmental factor (e.g., climate conditions, visualizations, and seasons) includes visual perceptions, such as clearness or fogginess on the motorway, and the time (either day or night) of the accidents studied. Road surface conditions include dry and wet surfaces related to breaking distance (Champahom *et al*., 2020b).

2) The road factor concerns pavement types (Pallavi and arpan, 2020) (e.g., concrete and asphalt concrete), which differ in terms of friction. The number of lanes influences the speed flow (Champahom *et al.*, 2020a). Another factor involves road geometry (e.g., straight or curvy), which relates to the speed of vehicles (Champahom *et al.*, 2019).

3) The traffic flow factor concerns the driver's perception. The weekday and traffic volume factors are related to the situation flow rate (Milton *et al.*, 2008; Malyshkina and Mannering, 2010; Wang *et al.*, 2011; Anastasopoulos, 2016). Truck involvement directly affects crash severity (Hong *et al*., 2019).

Accidents involving trucks tend to result in more severe accidents (Li-Yen and Fred, 1999; Lemp *et al.*, 2011), possibly due to the enormous, heavy trucks (Milton *et al.*, 2008). Thus, many scholars have specifically investigated crashes involving trucks. Al-Bdairi and Hernandez (2017) studied the injury severity of large truck-involved in run-off-road crashes. Osman *et al.* (2016) investigated crashes of large trucks in work zones resulting in injuries. Castillo-Manzano *et al.* (2016) examined the relationship between truck load capacity and traffic accidents. Chang and Chien (2013) conducted a study on drivers' injury levels in case of truck-involved accidents and focused only on large trucks (Zhu and Srinivasan, 2011). The study was conducted on injury levels caused by single- and multi-vehicle crashes involving trucks on rural highways (Chen and Chen, 2011; Girotto *et al*., 2016).

Structure Equation Modeling (SEM) and Measurement Invariance Analysis

This research examined the accident size, of which the variables cannot be directly measured. Thus, it was compulsory to have indicator variables.

SEM is a tool to measure the relationship between variables that cannot be directly measured, called latent variables (Lee *et al*., 2008). Each latent variable has structural data representing the relationship between multiple variables comprising direct or causal relationships, indirect or mediated relationships, associations, and roles of errors of measurements in models (Washington *et al*., 2011). Most research using SEM for analysis often involves behaviors, such as young drivers in at-fault crashes or traffic citations (Hassan and Abdel-Aty, 2013) or the use of technology resulting in distractions for drivers (El-Basyouny and El-Bassiouni, 2013). Studies using SEM to determine the influence of factors affecting accidents or their severity include a study on factors affecting motor vehicle crashes, which used the number of accidents and injury levels to indicate the dependent variables (O'Connor *et al*., 2017), as well as an investigation of crash risk resulting from driving behaviors analyzed by the personalities and attitudes toward traffic safety of bus drivers (Mallia *et al*., 2015).

The indicators of accident size consist of 1) the number of victims divided into three injury levels, including the number of minor injuries, serious injuries (i.e., those admitted to the hospital after an accident), and deaths. The causes of the three injury levels were the potential indicators of accident size, and there were many studies predicting accident costs due to the different values of the three mentioned injury levels (Thonghim *et al*., 2007), 2) the number of vehicles in each accident, as well the number of victims incurring damages in an accident (Lee *et al*., 2008).

Due to the differences in motorways, analyzing their differences required two models, which were measurements of invariance. In other words, we tested the parameter values of the measurement model, including thresholds, factor loadings, and residual variance to determine whether they were different or not.

The purpose of this research is to examine factors affecting accident size on motorways number 7 and number 9 in Thailand and compare the two models, which play important roles in freight transportation. The results can be used to develop new policies or improve road characteristics to reduce accident severity.

Methods

Structural Equation Modeling (SEM)

Elements of Structural Equation Modeling (SEM)

For the elements of SEM, as shown in Figure 2 (Wirachai, 1999), the groups of variables could be classified into two categories, exogenous and endogenous variables. Both groups consist of latent variables and observable variables. The structure of the SEM of the two sub-models consists of 1) the measurement model, which shows the relationship between the latent variable and observable variable used for indicating each latent variable, is a potential exogenous and endogenous measurement model, and 2) the structural model, which represents the relationship between the exogenous and endogenous latent variables. The details of the SEM are as follows.

$$\mathrm{X} = \Lambda_X \xi + \delta \tag{1}$$

Equation 1 is the calculation for the exogenous measurement model or the variables generally called independent variables, where X is vector
q×1. For the observable variable of latent variable X, Λ_X is the matrix of regression effects for the observable variable of the independent variable.

$$\mathrm{Y} = \Lambda_X \eta + \varepsilon \tag{2}$$

Equation 2 is the calculation for the endogenous measurement model or the group of variables generally called dependent variables, where Y is vector p×1 for the observable variable of the latent variable Y.

$$\eta = \beta\eta + \Gamma\xi + \zeta \tag{3}$$

Equation 3 is the calculation for the structural model, where η is vector m x 1 for the latent endogenous variable. The details of symbols are presented as shown in Table 2.

Estimation of Parameters

Parameters are estimated in SEM by many methods, such as unweighted least squares, maximum likelihood (ML), weighted least squares (WLS), and generalized least squares.

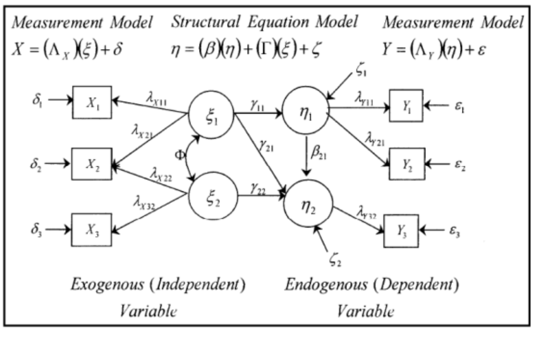

Figure 2. Elements of SEM

Table 2. Description of structural equation modeling

Symbol	Name	Description	Size
X	Esk	Vector of X Observe exogenous variables	q×1
Y	Wi	Vector of Y Observe endogenous variables	p×1
ξ	Xi	Vector of K Latent exogenous variables	n×1
η	Eta	Vector of E Latent endogenous variables	m×1
δ	Delta	Vector of measurement error term for observe variable X	q×1
ε	Epsilon	Vector of measurement error term for observe variable Y	p×1
Λ_x	Lamda-X	Matrix of regression effects for X on ξ	q×n
Λ_y	Lamda-Y	Matrix of regression effects for Y on 'Eta' η	p×m
Γ	Gamma	Matrix of causal effects from 'Xi' to 'Eta' η	m×n
B	Beta	Matrix of causal effects between "Eta" η	m×m
ζ	Zeta	Vector of measurement error terms	m×1
Φ	Phi	Covariance matrix between error terms for exogenous variable of 'Xi' ξ	n×n
Ψ	Psi	Covariance matrix between error terms for exogenous variable of 'Zeta' ζ	m×m
Θ_δ	Theta-delta	Covariance matrix between error terms for exogenous variable of 'Delta' δ	q×q
Θ_ε	Theta-epsilon	Covariance matrix between error terms for exogenous variable of 'Epsilon' ε	p×p

Remake : q = number of observe exogenous variable, p = number of endogenous variable, n = number of latent exogenous variable and m = number of latent endogenous variable.

Table 3. Descriptive statistic

Variable (value)	Motorway No.7 (Average)					Motorway No.9 (Average)				
	Frequency	No. deaths	No. serious injuries	No. minor injuries	No. involved	Frequency	No. deaths	No. serious injuries	No. minor injuries	No. involved
Visualization										
Clean (1)	2,098	0.04	0.11	0.46	1.80	1,549	0.04	0.12	0.34	1.71
Other (Raining, Dust and mist) (0)	274	0.04	0.08	0.49	1.62	446	0.01	0.07	0.26	1.79
Road surface										
Wet (0)	313	0.02	0.07	0.48	1.63	510	0.01	0.06	0.24	1.76
Dry (1)	2,059	0.04	0.12	0.46	1.80	1,485	0.04	0.12	0.35	1.72
Time										
Day (1)	1,292	0.03	0.10	0.46	1.81	1,104	0.03	0.10	0.32	1.78
Night (0)	1,080	0.05	0.12	0.47	1.73	891	0.04	0.11	0.32	1.67
Pavement of road										
Asphalt concrete (1)	2,207	0.03	0.1	0.47	1.77	1,916	0.03	0.11	0.31	1.74
Concrete (0)	165	0.10	0.25	0.39	0.18	79	0.04	0.11	0.49	1.54
Number of lane										
4 (2)	1,852	0.04	0.12	0.49	1.77	1,808	0.04	0.11	0.31	1.71
8 (4)	520	0.02	0.07	0.35	1.80	157	0.01	0.04	0.37	1.83
Road geometric										
Straight (1)	2,061	0.04	0.11	0.47	1.81	1,626	0.04	0.12	0.33	1.76
Other (Curve, Ramp, Intersection etc.) (0)	311	0.03	0.12	0.44	1.57	369	0.02	0.07	0.26	1.60
Truck involvement										
No (0)	1,610	0.03	0.10	0.43	1.62	1,326	0.03	0.07	0.30	1.53
Yes (1)	762	0.05	0.14	0.52	2.10	669	0.04	0.18	0.37	2.12
AADT (Vehicles/day)										
42,734	128					12	0.07	0.13	0.16	1.56
46,851	643	0.03	0.14	0.56	1.60	637				
51,857	428					111	0.02	0.12	0.30	1.55
51,944	132	0.06	0.09	0.47	1.61	146				
57,651	333	0.03	0.06	0.32	2.11	481				
93,287	708					608	0.03	0.10	0.35	1.82
Day										
Weekday (0)	1,706	0.04	0.11	0.45	1.78	1,476	0.03	0.10	0.29	1.74
Holiday (1)	666	0.03	0.12	0.48	1.77	519	0.04	0.13	0.41	1.69

Remark : Motorway No.7 = 2,372 cases, Motorway No. 9 = 1,995 casest

Nevertheless, ML is mostly used as an estimator because ML is suitable for the high number of samples, while the chi-square test of each variable must have a normal distribution as well. However, the variables in this research were not all in a normal distribution. Most of them were discrete data and dichotomous outcomes, so it was necessary to use WLS, called WLSMV in Mplus (Yu, 2002; Lee *et al*., 2008), as an estimator.

The concept of parameter estimation in SEM is the prediction from the population covariance matrix of the observable variable ($\sum$), which can be identified in terms of unknown parameter (θ). The unknown parameter consists of $\mathrm{B}, \Gamma, \Phi,$ and Ψ matrices, which are the elements of the covariance matrix in the model or $\sum \ = \sum(\theta)$. Thus, the parameters of θ could be predicted by minimizing the discrepancies between the sample covariance matrix and the population covariance matrix, which acquired $\sum(\theta)$.

For considering the variables without normal distribution or dichotomous outcomes, WLS was

Table 4. Goodness-of-fit test

Measure	Defining	Fit indices
Chi-square statistic (x^2) Degree of freedom (*df*) P-Value		Significant p-values expected*
x^2/df		Value <3**
CFI	$\mathrm{CFI} = 1 - \frac{\max[(X^2_{H_0} - df_{H_0}), 0]}{\max[(X^2_{H_0} - df_{H_0}), (X^2_b - df_b)]}$	Above 0.92*
TLI	$\mathrm{TLI} = \frac{X^2_b/df_b - X^2_{H_0}/df_{H_0}}{(X^2_b/df_b) - 1}$	Above 0.92*
WRMR	$WRMR = \sqrt{\frac{2NF(\hat{\boldsymbol{\theta}})}{e}}$	Value < 1.00***
RMSEA	$RMSEA = \sqrt{\max\left[\left(\frac{2F(\hat{\boldsymbol{\theta}})}{d} - \frac{1}{N}\right), 0\right]}$	Values < 0.07 with CFI of 0.92 or higher*
Remark:		

* (Hair Jr *et a*l., 2010), ** (Washington *et al*., 2011), ***(Yu, 2002)
Tucker-Lewis Index (CFI) and Comparative Fit Index (TLI): Where df_b and df_{Ho} are the degrees of freedom for the baseline and the hypothesized (under H0) models, respectively
Weighted root-mean-square Residual (WRMS): where *e* is the number of sample statistics,
$F(\hat{\theta}) = F_{WLS}(\theta) = \min\left[(\frac{1}{2})s - \sigma(\theta)\right]'W^{-1}[s - \sigma(\theta)]$ which is the minimum of the weighted least squares (WLS) fitting function
Root-mean-square error of approximation (RMSEA): where d denotes the degrees of freedom of the model, and $F(\hat{\theta})$ is the minimum of the fitting function $F(\theta)$

used to calculate the fit function by predicting θ by minimizing the fit function:

$$F_{WLS}(\theta) = [s - \sigma(\theta)]'W^{-1}[s - \sigma(\theta)] \qquad (4)$$

where s is the vector of $\frac{1}{2}(p+q)(p+q+1)$ elements of the sample covariance matrix, W^{-1} stands for $\frac{1}{2}(p+q)(p+q+1) \times \frac{1}{2}(p+q)(p+q+1)$ positive-definite weight matrix, and $\sigma(\theta)$ denotes the corresponding same-order vector of $\sum(\theta)$.

Measurement Invariance Analysis

The means comparison of the regression coefficients estimated from two population groups, such as a country or culture, were conducted by supposing that the outcome variables of the two models were equal. In this research, the variables included discrete exogenous variables (categorical variables). The steps of comparison were as follows: 1) construct a model called the configural equivalence model starting from the determination of loadings and thresholds across groups; then set factor mean values of the two groups as 0, and fix residual variance as 1 in both two groups; 2) build a full equivalence model determining setting factor loadings and threshold constraints to be equal across groups; and determine the residual variance to have stable value as 0 in one group, while the others have self- regulating values (Muthén and Muthén, 2012). For the interpretation of measurement invariance, the difference of the chi-square statistic (x^2) and the degree of freedom (*df*) should be considered. If the two values are statistically significant, the models of the two motorways are different (Muthén and Muthén, 2012).

The Model Fit Indices

To check whether the relationship between the latent variables (endogenous and exogenous) was sufficiently adequate to analyze SEM or not, the values indicating the model parameters were examined, such as Tucker-Lewis Index (CFI)>0.95, Root-mean-square error of approximation (RMSEA)<0.05 (Mulaik and Millsap, 2000). The models were developed relevant to the empirical data on the values of the goodness-of-fit statistics, of which the standard criteria were accepted, as shown in Table 4 (Yu, 2002; Hair *et al*., 2010; Kenny, 2016).

Results

Crash Data Reports

The data used in this research were supported by the Intercity Motorways Division, Department of Highways. The accident data occurred on motorways number 7 and number 9 during the 2010-2016 period. Latent variables used to consider the relationship with accident severity were constructed based on the ground theory of accident occurrences consisting of the traffic flow, environmental, and road factors (Hassan and Al-Faleh, 2013). The observable variables in this research were designated as dummy variables. The details of the measurement model are as follows.

1) "Traffic flow factors" concern drivers' perceptions and vehicles consisting of "truck involvement" divided into the accidents with and without trucks. The annual average daily traffic (AADT) is a continuous variable based on the roads (motorway route) and ranges of roads, which were considered according to the number of cars paying at a toll booth. A "weekday" means the consideration to be weekdays or holidays.

2) "Environmental factors" include a "visualization" factor having two values, "clean" and "others" (rain, dust, or mist), a "road surface" factor comprising dry and wet conditions, and a time factor consisting of two periods of time, day and night.

3) "Road factors" encompass two pavement types, including asphalt and concrete pavement. The number of traffic lanes is divided into two types, including four-lane roads and those with more than four lanes. "Road geometry" consists of 1 = straight and 0 = other (e.g., curve, ramp, intersection, etc.).

4) The measurement variable of "accident size" consists of four variables, which include the number of deaths, serious injuries, minor injuries, and vehicle involvement. They are all ordinal scale.

Table 3 shows the number of injuries, fatalities, and the average number of vehicle involvement distributed by different variables used for analysis. The variable having the highest average is "truck involvement," and the accidents occurring at night is 0.05 for motorway number 7 and 0.04 for motorway number 9. For the number of injuries on motorway number 7, the highest incidence was on concrete road surfaces, while for motorway number 9, it was the truck-involved accident variable.

Model Fit Indices

The goodness-of-fit measure of the two models was judged by the criteria shown in Table 4 and the values from the model prediction shown in Table 5. For motorway number 7, it was found that the value of chi-square statistics = 96.56, degree of freedom = 50, significant at < 0.000, and the ratio of $\chi 2/df$ was found to be 1.93, which was an appropriate ratio (less than 3). The CFI and TLI values equal 0.999 and 0.998, respectively (where appropriate value should be more than 0.95). The RMSEA value, which should be less than 0.07 (Hair Jr *et al*., 2010), is at 0.02. The WMSEA value, which should be less than 1, equals 0.994 (Yu, 2002). For motorway number 9, $\chi 2$ is 92.716, and df is 50. The CFI and TLI values are 0.984 and 0.944, respectively. The RMSEA and WRMR values are 0.019 and 0.972, respectively. Based on the statistical properties of the indicators, this model can be considered a good fit.

For the consideration of measurement invariance (MI) from the difference of the chi-square value (42.96) and df (11) of the configural equivalence model and the full equivalence model, the chi-square value has a statistical significance (p<0.000). One could therefore infer that the models of accident size occurring on motorway number 7 and number 9 were different in terms of statistical significance.

Structural Equation Modeling (SEM) Results

Considering the significance level of factor loadings (γ) that resulted from the SEM model, as shown in Table 6, for motorway number 7, it was found that the factor that most affected "accident size" was the "traffic flow factor" ($\gamma = 0.376, p < 0.000$). For observable variables used for measurement, "truck involvement" (reference variable) was determined first, followed by AADT ($\lambda = 0.845, p < 0.000$). The second factor affecting "accident size" was the road factor ($\gamma = 0.082, p < 0.1$), of which the indicator having the highest factor loading was "pavement" (reference variable), followed by the number of lanes ($\lambda = -0.226, p < 0.05$) and "road geometry" ($\lambda = 0.123, p < 0.05$). The factor that least affected accident size was the environmental factor ($\gamma = 0.067, p < 0.05$), with the highest factor loading indicator "visualization" (reference variable), followed by "road surface" ($\lambda = 0.978, p < 0.05$) and "time" ($\lambda = 0.259, p < 0.05$).

In terms of motorway number 9, only two latent variables significantly impacted accident size. 1) The first was the environmental factor ($\gamma =$

Table 5. Model fit indices of invariance test

	x^2 statistic	*df*	P-Value	x^2/ *df*	RMSEA	CFI	TLI	WRMR	Delta x^2	Delta-*df*	P-value
Single model											
Motorway No.7 Model	96.560	50	0.000	1.93	0.02	0.999	0.998	0.994			
Motorway No.9 Model	92.716	50	0.000	1.85	0.019	0.984	0.944	0.972			
Multi-group analysis											
Configural equivalence (Base model)	117.865	55	0.000	2.14	0.023	0.994	0.99	1.424			
Full equivalence (Full model)	160.825	66	0.000	2.43	0.026	0.990	0.987	1.653	42.96	11	<0.000

$0.161, p < 0.000$). The indicator properties consisted of "visualization" (reference variable) "road surface" ($\lambda = 0.988, p < 0.000$), and "time" ($\lambda = 0.176, p < 0.000$). 2) The second was the traffic flow factor ($\gamma = 0.072, p < 0.05$). The properties of the measured variables consisted of "truck involvement" (reference variable), "AADT" ($\lambda = 0.092, p < 0.01$), and "weekday" ($\lambda = -0.119, p < 0.01$).

Discussion

All the indicators of the dependent variable were significant in both models. However, there was some difference in the order of the factor loadings. For motorway number 7, it was found that the number of minor injuries and deaths were the highest. Therefore, the crash size in this route should be measured by the number of injuries and deaths. Conversely, for the model of motorway number 9, the crash size should be measured by the number of minor injuries, the number of vehicles involved, and the number of serious injuries. In addition, the number of vehicles involved could indicate the crash size because crashes are indicated by the number of vehicles in a crash, which relates to the number of injuries. This result is similar to the findings of Lee *et al*. (2008), who noted that the number of vehicles significantly indicates the accident size factor.

From the results of MI, we determined that the models of motorways number 7 and number 9 were different. For example, the measurement model regarding the road factor only has significance for route number 7, whereas for the measurement model regarding the traffic flow factor, the weekday variables are only significant for route number 9. Thus, the policy recommendations for reducing the severity of accidents are also different. The details of these findings are presented in the following section.

For motorway number 7 (Figure 3), the traffic flow factor resulted in the most severe injuries. The indicator of this factor, starting from accidents involving trucks, suggested that accidents with trucks were more serious than those without trucks. This finding relates to the work of Zhang, Yau, and Chen (2013), who found that vehicles transporting goods have higher risks since the truck size is much larger than that of personal cars. When accidents occur, the relatively violent strike causes drivers to sustain more injuries. Moreover, the accident size after crashes might block traffic lanes, possibly leading to subsequent accidents. Furthermore, AADT was positively significant,

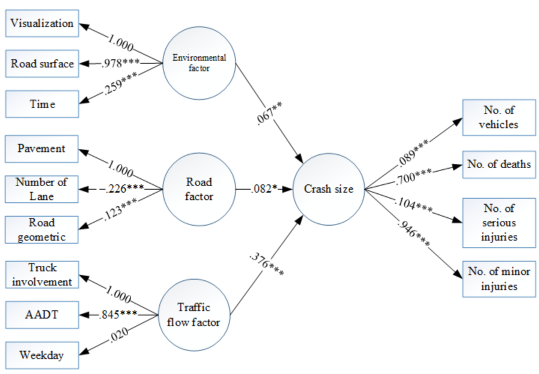

Figure 3. Crash size model of route no.7
***Note.* * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01**

Table 6. Standardized SEM results

Variables	Motorway No.7			Motorway No.9		
	Estimate	**S. E**	**P-Value**	**Estimate**	**S. E**	**P-Value**
Environmental factor by						
Visualization	1.000	0.000	*	1.000	0.000	*
Road surface	0.978	0.005	0.000	0.988	0.002	0.000
Time	0.259	0.038	0.000	0.176	0.037	0.000
Road factor by						
Pavement	1.000	0.000	*	1.000	0.000	*
Number of lanes	-0.226	0.049	0.000	0.036	0.034	0.299
Road geometric	0.123	0.044	0.000	4.134	3.597	0.250
Traffic flow factor by						
Truck involvement	1.000	0.000	*	1.000	0.000	*
AADT	0.845	0.047	0.000	0.092	0.036	0.009
Weekday	0.020	0.025	0.435	-0.119	0.039	0.002
Accident size by						
Number of vehicle	0.089	0.026	0.001	0.403	0.009	0.000
Number of deaths	0.700	0.176	0.000	0.096	0.042	0.023
Number of serious injuries	0.104	0.030	0.001	0.357	0.030	0.000
Number of minor injuries	0.946	0.271	0.000	0.414	0.019	0.000
Accident size on						
Environmental factor	0.067	0.027	0.012	0.161	0.037	0.000
Road factor	0.082	0.046	0.072	0.042	0.038	0.274
Traffic flow factor	0.376	0.097	0.000	0.072	0.033	0.028

Remark * is reference variable in each latent variable.

a finding supported by a study by Sun *et al*. (2016). The second factor that caused severe accidents with a approximate loading factor including the road factor and the environmental factor. When considering the measurement model, it was found that clean visualization and a dry road surface resulted in an increase in accident severity. These accidents possibly resulted from the high speed of driving when the drivers were in such conditions. This finding is in line with the study of Lee *et al.* (2008), who found that the increasing speed relates to accident size. Regarding road factors, asphalt road surfaces caused more accident injuries than those on concrete road surfaces because the friction coefficient between wheels and asphalt road surfaces is lower (Ramsdale, 2017), causing longer braking times and high speeds during crashes.

Some factors were not significant because there were high standard errors. For example, the effect of the weekday factor (λ = 0.020, S.E. = 0.25) was small. Thus, the accident size for route number 7 did not vary on weekdays and weekends. The traffic volume does not differ because freight vehicles still operate even on weekends.

The model of accident size on motorway number 9 was different from that on motorway number 7 (Figure 4). In other words, the two available latent variables, which resulted in larger accidents, included the environmental factor (the highest loading factor). Considering the measured model, it was found that the accidents occurring in clear weather on dry pavement increased accident size. The optimal conditions make drivers confident, so they drive at higher speeds. The traffic flow was another important factor. Similar to motorway number 7, having trucks involved in accidents also caused larger accidents on motorway number 9. Moreover, differences exist regarding accidents on weekdays and holidays. The results of the model suggest that, on weekdays, the accident size was larger than that on holidays. This finding

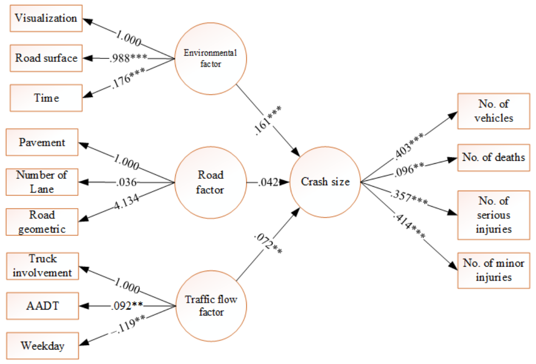

Figure 4. Crash size model of route no.9
***Note.* * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01**

resembles that of Yu *et al*. (2016), who found that more traffic quantity resulted in more risks of accidents. The feasible cause is that motorway number 9 was built near the capital of a country with high employment, causing a reasonably high quantity of vehicles on the roads on weekdays (Hassan and Al-Faleh, 2013).

The factors in this model with high error terms include 1) the number of lanes, a result similar to the findings of Wu, Zhang, Zhu, Liu, and Tarefder (2016), who found that the number of lanes was insignificant for crash severity, and 2) road geometry, a finding consistent with a study by Hong *et al.* (2019), who found that road geometry was insignificant in truck-involved crashes on expressways.

Conclusion and Implementation

Intercity motorways play important roles in freight transportation. This research aimed to understand the factors that affect accident size on motorways. The model results provide guidelines for reducing the severity of accidents occurring on intercity motorways in Thailand and promote sustainable freight transportation. The research has studied accident severity analyzed by structural equation modeling (SEM) because accident size cannot be directly measured. The measured variables include the number of minor injuries, serious injuries, deaths, and the number of vehicles involved in the accidents. The independent variables consist of environmental, road, and traffic flow factors. To consider the difference between two motorways, MI analysis was used to test the difference in the analysis of the results.

The results of the invariance analysis showed that the models of accident severity on motorways number 7 and number 9 were different. The policies recommended for reducing the accident severity are both similar and different as follows.

The measures, which should be implemented to prevent accidents on the two motorways, consist of two issues : 1) the management of truck driving, including policies such as increasing law/traffic enforcement to restrict the use of truck lanes, and 2) the management of car users' speed on motorways. For example, the operation can be carried out by determining the maximum speed close to the minimum speed according to Thairoads (2014) study to reduce victims and their levels of injuries.

The results indicate that the parameters in both models are different. For motorway number 7, road organizations could consider reducing accident sizes by increasing the construction of concrete surface roads. Regarding motorway number 9, the promotion of suitable driving speed should be increased, especially on weekdays.

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Limitations and Future Research

This study analyzed the road traffic accident data on intercity motorways in Thailand. To apply the results in other countries, researchers must consider the consistency of road conditions, such as speed limits, vehicle types, land-use policies, and traffic volume. Another limitation of this study is the factor of driver characteristics and driver behaviors, especially truck drivers who drive freight vehicles. Future research could focus on truck driver behavior to create policies to use for third-party logistics providers.

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