ANALYSIS OF FACTORS AFFECTING REAR-END CRASH SEVERITY USING STRUCTURAL EQUATION MODELING

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Abstract

Road accidents regularly cause a high number of fatalities. Thailand's road accident fatality rate of 32.7 of every 100,000 people ranks the ninth in the world. Surprisingly, same-direction collisions comprise the highest proportion of crashes leading to fatality. To determine how best to minimize the number of fatalities and injuries, this research uses structural equation modeling (SEM) to examine factors affecting rear-end collisions' severity. According to SEM results, the driver factor had the greatest effect on collision severity, followed respectively by road and environmental factors. After assessing relevant factors, this study suggested that stakeholder organizations should play an important role in road design and maintenance and in driver training. The study also discussed driving and road policies in Thailand and other developed countries.

Keywords: **Rear-end collision, highway, latent variables, structural equation modeling, crash size**

Introduction

In 2016, road accidents caused about 1.35 million deaths in over 180 countries worldwide, and developing countries broke a record for the highest number of deaths (WHO, 2018). Thailand ranked ninth in the world, in the number of deaths caused by car crashes per 100,000 people.

At this writing, Thailand is undergoing agricultural, commercial, and industrial expansion, with the Thai government supporting improvements to make road transportation faster, safer, and more comfortable. Expansion has led to increased use of personal vehicles, which is one factor causing both road accidents and significant losses to the government and the private sector (Office of Transport and Traffic Policy and Planing, 2014).

In Thailand, the Royal Police have reported on road accident trends. In 2006, 110,685 road accidents caused 12,691 deaths. This number decreased until 2013, and then increased continuously from 2013 to 2019. In all road accidents reported by the Royal Police in 2019, the Department of Highways (DOH) held responsibility for 18 percent, in which

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the proportion of casualties was 31 percent and the proportion of deaths was 26 percent. Accident costs reported by the Royal Police in 2019 approximated 323,895 million baht, while the DOH's responsibility was 57,154 million baht because 20 percent of expenditures were estimated from classifications of types of injuries experienced by passengers and drivers, including deaths, disabilities, serious injuries, and minor injuries (Department of Highway Thailand, 2020). Thus, highways, under DOH control, must provide approaches for reducing rates of severe injuries caused by road accidents.

Of 17,554 highway crash in 2019, as classified by types of crashed, the most crash type is "run off the road on a straight road." 7,488 cases. Followed by "crashes on the road in the same direction" or "rear-end crash" 5,151 cases. However when considering the number of deaths due to rear-end crash, it was found that the highest number was 721 cases, (Department of Highway Thailand, 2020).

A rear-end collision, in which a following vehicle crashes into the back of a leading vehicle, is the most frequent type of road accident. There may be one or more vehicles involved because when these accidents occur, traffic levels are often heavy, and vehicles move at high speeds in constricted spaces. Even so, most rear-end collisions are not serious. Their severity, as affected by speed and vehicles size and weight, affects resulting fatalities. Causes of rear-end collisions include abrupt changes in front of other cars following too closely behind, rapid changing between traffic lanes or passing, and drivers' awareness and skills. Factors in rear-end collisions are: 1) "ducking," in which small vehicles crash into the rear of large, massive vehicles, possibly causing driver fatality; 2) carrying items protruding from the rear of vehicles, possibly causing rear-end collisions if the driver behind does not notice protruding items; 3) broken-down cars parking and obstructing traffic lanes without signaling other road users; and 4) other factors such as driving slowly in the right lane or driving at night (Ministry of Interior Department of Disaster Prevention and Mitigation, 2014). Lerdworawinich (2000) has studied ways of reducing risks and severity of rear-end collisions on Thai highways. He has experimented with installation of a tailgating treatment on roads to help drivers increase their awareness of the distance between their vehicle and the vehicle in front of them. Lerdworawinich (2000) found that the tailgating treatment can reduce the risk of rear-end collisions. Iamtrakul (2008) studied risk factors causing rear-end collisions in Phra Nakhon Si Ayutthaya Province, using and analyzing questionnaires and collecting data from case studies of rear-end collisions classified into serious and non-serious cases.

In Thailand, aside from two studies on rear-end collisions, no studies have used historical statistics to build a model for analyzing factors affecting the number and severity of injuries. Because these factors cannot be directly measured, the severity of injuries was divided into three levels: minor injury, serious injury, and fatality. The structural equation model's (SEM's) ability to determine the relationship between latent variables that cannot be directly measured, such as "severity of accidents" is the "structural model (path analysis)," and latent variables measured by observed variables are "measurement models."

SEM has been applied to analyze a variety of accidents in other countries. The model was not designed, however, to find and predict factors on Thai highways affecting rear-end crash severity as indicated by numbers of deaths and serious and slight injuries. When these factors are determined, they can be used for road engineering design and driver training. According to model results in this research, a variety of variables have never been studied in any other research, for example, crash types, traffic quantity, truck percentage, and personal factors such as alcohol use, safety equipment use, and so on. This study contributes by using the model's results to propose policy that can reduce rear-end crash severity.

Literature Review

This research follows global research trends that attend to road accidents as the most frequently occurring type of transportation accident. The rear-end collision is the type most frequently studied, with many studies having discussed factors that affect the probability of rear-end collisions, such as driver age. Methods used here examine the nonlinear relationship between driver age and log odds (fault or no-fault driver in rear-end collisions). The study separated driver age into 7 ranges: <26 years; $26 \le$ age ≤ 35; $36 \le$ age ≤ 45; $46 \le$ age ≤ 55; $56 \le$ age ≤ 65; $66 \le$ age ≤ 75; and age> 75 years. Smooth function results have shown young and old drivers higher risk of fault in rear-end collisions than middle-aged drivers. The study analysis is based on rear-end collisions' pre-crash conditions, which consider leading vehicles' speed. Types of rear-end collisions include "stopped in road," "decelerating speed," and "normal speed" (Ma and Yan, 2014). Comparisons between teen and adult rear-end collisions have also been undertaken (Seacrist *et al*., 2016). Rear-end crash potential has been assessed in roads' work zone merging areas (Weng *et al*., 2014). Chen *et al*. (2016a) analyzed factors affecting severity of driver injury by employing several factors including the time of the accident. Oh *et al*. (2006) studied rear-end collision cases by installing a loop detector to collect and survey data from traffic lights as a means of examining driving behavior and predicting safe stopping distances to reduce rear-end collisions. Joon-Ki *et al*. (2007) established a model for predicting the possibility of rear-end collisions on freeways (Pande and Abdel-Aty, 2008). Liang *et al*. (2010) studied multi-agent and driver behavior in rear-end collision notices. Among four warning factors, they included driver repository (e.g., vehicle type), rear-end collision cases, an environment model, and a driving behavior model. These factors resemble those in a study by Yan and Radwan (2009) who studied rear-end collisions with trucks' presence. Meng and Weng (2011) have examined risks of rear-end collisions in work zones, finding that trucks had greater chances of rear-end collisions than personal vehicles. Furthermore, the increased proportion of heavy trucks on the road and the amount of traffic per lane have increased chances of rear-end collisions. A policy of a vehicle merging area prior to reaching a work zone has thus been proposed. In 2015, a key study predicted rear-end collisions in work zones (Weng *et al*., 2015). Apart from risks of accidents in work zones, studies of rear-end collisions at crossroads were also conducted (Wang *et al*., 2003; Cunto and Saccomanno, 2009; Shahi *et al*., 2009; Chu *et al*., 2015). Meng and Qu (2012) compared crossroads with and without countdown traffic lights (Ni and Li, 2014). Analysis of rear-end at the roundabout (Gallelli *et al*., 2019). Wan *et al*. (2013) studied rear-end and lane-changing collisions through car-following behavior, which explains driver behavior while following leading cars. Factors were environmental, including visual perception (clearness, fog, or snow); road surface conditions; and driver behavior. Studies of other types of rear-end collisions included effectiveness of low-speed autonomous emergency braking in rear-end collisions (Fildes *et al*., 2015) and the proportion of low-speed leading cars affecting rear-end collisions (Nishimura *et al*., 2015).

Chen *et al*. (2015) studied levels of driver injuries resulting from rear-end collisions in New Mexico from 2010 to 2011, using a multinomial logit model to determine factors affecting levels of driver injuries from contribution factors. Injuries were divided into three levels: no injury, injury, and fatality; contribution factors included driver behavior factors (e.g., age, gender), vehicle factors (e.g., vehicle type); road physical features (e.g., road function, pavement); and environmental factors (e.g., light conditions, weather conditions). Under environmental factors, the availability of lighting could reduce the number of fatalities. In 2016,

Table 1. Variables codes and descriptions

Code	Description	Value
Driver factors		
V1	Large vehicle size involvement (6 wheeled truck and larger)	1 = Yes, 0 = other
V2	Gender of driver	1 = Male, 0 = Female
V3	Age of driver from 26–35 Years	1 = Yes, 0 = other
V4	Age of driver from 36–45 Years	1 = Yes, 0 = other
V5	Age of driver from 46–55 Years	1 = Yes, 0 = other
V6	Driver used safety equipment (seat belt, helmet)	1 = Yes, 0 = other
V7	Drunk driver involved	1 = Yes, 0 = other
V8	Exceeding the speed limit	1 = Yes, 0 = other
V9	Order of vehicle involvement	Counts
Road factors		
V10	Per cent trucks	Continuous
V11	Traffic direction separated by road median (barrier, etc.)	1 = Yes, 0 = other
V12	The road was not being repaired	1 = Yes, 0 = other
V13	The road was asphalt or concrete pavement	1 = Yes, 0 = other
V14	Road horizontal alignment	1 = Straight, 0 = Curve
V15	Road graded	1 = slope, 0 = other
V16	Rear-end collision happened in interior lane	1 = Yes, 0 = other
V17	Rear-end collision happened at intersection	1 = Yes, 0 = other
V18	Log of AATD	Continuous
V19	Number of lanes	0 = Rather than 4 lanes, 1 = other
Environmental factors		
V20	Collision happened at night in low-light conditions	1 = Yes, 0 = other
V21	Visualization of drivers as accident	1 = Clean, 0 = other
V22	Time of collision	1 = Day, 0 = Night
V23	Status of road surface	1 = Wet, 0 = Dry
Rear-end factors		
V24	Leading vehicle was using normal and stable speed	1 = Yes, 0 = other
V25	Leading vehicle has stopped	1 = Yes, 0 = other
Crash size severity factors		
V26	Numbers of fatalities	Counts
V27	Number of persons seriously injured	Counts
V28	Number of persons slightly injured	Counts

studies were conducted using a decision table/Naïve Bayes (DTNB) hybrid classifier to analyze levels of driver injuries from rear-end collisions (Chen *et al*., 2016b). Das and Abdel-Aty (2011) studied frequency of rear-end collisions and levels of injuries on main roads in urban cities by establishing a genetic programming (GP) model. In the injury levels model, they found that high vehicle speeds resulted in greater severity of injuries. For road surfaces with a high friction coefficient, traffic islands could decrease severity of injuries. Sullivan and Flannagan (2003) studied fatalities resulting from rear-end collisions by comparing crashes that occurred both in lighted and unlighted conditions, finding that collisions that occurred without light had two times more fatalities than those in lighted conditions, because drivers could not abruptly decrease speed in low visibility (Abdel-Aty and Abdelwahab, 2004). Qi *et al*. (2013) studied injury levels in rear-end collisions at work zones, finding that nighttime rear-end collisions increased the level of injuries. Wiacek *et al*. (2015); Piccinini *et al*. (2017); Champahom *et al*. (2019); Champahom *et al*. (2020b) found that rear-end collisions by heavy vehicles increased chances of fatalities. Mohamed *et al*. (2017) found that rural roads and violation of determined speed limits resulted in more severe rear-end collisions.

Variables found and used in previous studies are illustrated in Table 1. New variables in this research consisted of two groups (Table 2) as follows:

Group 1. Using SEM, as used in previous research collecting all crash types to study accident severity, this study focused only on rear-end collisions. Added variables were crash types, safety equipment uses, and large truck proportion (Lee *et al*., 2008; Kim *et al*., 2011; Hamdar and Schorr, 2013; Hassan and Al-Faleh, 2013; Schorr and Hamdar, 2014).

Group 2. The study of only rear-end collisions, especially injury severity levels they caused (e.g., Georgi *et al*., 2009; Yuan *et al*., 2017) found that no research has investigated rear-end crash severity by measuring it as a latent variable. New variables in this research included road maintenance, consideration of rear-end crash types affecting crash size, and other variables, including rear-end crashes on straight roads with drivers' sight distance affected, higher speed on main roads than on parallel roads, sudden stops in intersections, and traffic quantity potentially affecting driving speed that reduced rear-end crash size. The studies of Champahom *et al*. (2019); Champahom *et al*. (2020b) are similar with this study, however they were not considering based on the crash size which indicated by the number of persons in each severity level.

Variables Discussion

For measuring rear-end collisions on Thai highways, the following indicators are used. Indicators of rear-end crash severity can be measured by injury at three levels: (i) number of deaths, referring to casualties who die on the road or in the hospital; (ii) serious injuries, meaning an injury that cannot heal in less than 3 weeks; (iii) slight injuries, meaning an injury that can heal in less than 3 weeks. For considering the effect of contributing factors for all injury levels, rear-end crash severity is set as a latent variable.

1) Driver factor indicators are as follow: (i) vehicle types and truck sizes that might increase collisions' numbers and injury levels and truck sizes related to speeding; (ii) drivers' ages divided into three groups (26-35, 36-45, and 46-55 years) (Ma and Yan, 2014) affecting drivers' healing, with younger drivers healing more quickly than older drivers; and (iii) driver genders when female drivers have lower perception time than male drivers. Other factors included safety equipment use, exceeding speed limits, and order of vehicle involvement (Lee *et al*., 2008).

2) The road factor is divided into three categories: (i) divided highways with directions separated by a median to reduce accidents and make drivers pay more attention; (ii) work zone safety signs to make drivers reduce their vehicles' speed; (iii) road surfaces, for example, the variety of asphalt and concrete that could affect vehicles' speed (Das and Abdel-Aty, 2011). Other variables included rear-end crashes on straight roads, but with driver sight distance affected, higher speed on main roads than on parallel roads, sudden stops in intersection areas (Dong *et al*., 2016; Koohathongsumrit and Meethom, 2018), and traffic quantity potentially affecting speeds that reduced accident severity.

3) Environmental factors were divided into three categories: (i) lighting conditions on road, which could affect the number of accidents (Qi *et al*., 2013); (ii) accident time, with drivers often increasing their speed in daylight because of the clear vision; (iii) weather affecting driving speed, and (iv) road surface conditions that might affect braking distance (Yan and Radwan, 2006).

4) In a rear-end collision case involving two vehicles, vehicular speed could be the important factor. Indicators of rear-end collision are as follow: (i) leading vehicle speed when struck from behind by other vehicles even though the leading vehicle is traveling at normal speed; (ii) reduced speed of leading vehicles hit from behind by other vehicles because of reduced speed on the road; and (iii)

Table 2. Gaps of Literature

Work/variables (Authors, Year)	V1	V2	V3-V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25
This Study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(Lee *et al*., 2008)*	✓	✓	✓	-	-	-	-	-	-	✓	✓	✓	✓	✓	-	-	-	✓	✓	✓	✓	✓	✓
(Kim *et al*., 2011)*	-	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
(Hamdar and Schorr, 2013)*	-	✓	✓	-	-	-	-	-	-	-	✓	✓	✓	✓	-	-	-	✓	✓	✓	-	-	-
(Hassan and Al-Faleh, 2013)*	✓	-	✓	-	✓	-	-	✓	-	-	-	✓	✓	✓	-	-	-	-	✓	✓	-	-	-
(Schorr and Hamdar, 2014)*	-	✓	✓	-	-	✓	-	✓	-	✓	-	✓	-	-	-	✓	-	-	-	✓	-	-	-
(Ma and Yan, 2014)**	-	✓	✓	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	✓
(Chen *et al*., 2015)**	✓	✓	✓	✓	✓	✓	-	-	-	-	✓	✓	✓	-	-	-	-	✓	✓	✓	✓	-	-
(Chen *et al*., 2016)**	✓	✓	✓	✓	✓	✓	✓	-	-	-	✓	✓	✓	-	-	-	-	✓	✓	✓	✓	-	-
(Das and Abdel-Aty, 2011)**	-	-	-	-	-	✓	-	-	✓	-	✓	✓	-	-	✓	✓	-	✓	✓	✓	✓	-	-
(Yan and Radwan, 2009)**	✓	✓	✓	-	✓	-	-	-	✓	-	-	-	-	-	-	-	-	✓	✓	✓	-	-	-
(Georgi *et al*., 2009)**	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	✓	✓	-	-
(Abdel-Aty and Abdelwahab, 2004)**	✓	✓	✓	✓	✓	✓	-	-	-	-	-	✓	✓	-	✓	-	-	✓	✓	✓	✓	-	-
(Qi *et al*., 2013)**	✓	✓	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	✓	✓	✓	✓	-
(Christopher, James, and Dinesh, 2014)**	✓	-	-	-	✓	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
(Mohamed *et al*., 2017)**	✓	✓	✓	-	✓	✓	-	-	-	-	-	-	-	-	✓	-	✓	✓	✓	✓	✓	-	-
(Yuan *et al*., 2017)**	✓	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	✓	✓	✓	✓	-	-
(Champahom *et al*., 2019)**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(Champahom *et al*., 2020b)**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Remark: * denotes literature in SEM analyses of accident size. ** denotes studies in analysis of rear-end crash severity

stopped vehicles hit from behind by other vehicles (Ma and Yan, 2014).

Methods

Data Collection

This study's data collection included gathering original data and collecting data about rear-end collisions from the Department of Highway (DOH): For this research, data for analysis of highways in Thailand were drawn from 2011 to 2015 (B.E. 2554-2558). Data were originally surveyed by area permanent officers who collected details of highways accidents: date, highway data, accident characteristics, crash type, number of accidents, and injury severity levels. Data were subsequently collected in the Highway Accident Information Management System (HAIMS). Consequently, data selected for this study involved only rear-end collisions with consideration of crash types, and data of drivers in accidents were used to establish the model. Selection of rear-end crash data produced 1,902 cases and 4,134 accident cars and drivers.

Analysis Method

This research studied factors affecting severity of injury to drivers and passengers using data from the Department of Highway (DOH) by employing a structural equation model (SEM), in which main elements include an exogenous variable and an endogenous variable, that is, a latent variable and an observed variable. Because a latent variable cannot be directly measured, it is instead measured by using the observed variable. The subordinate model in a SEM is called the measurement model when considering the latent variable through each observed variable and the structural model when considering a latent variable affecting another latent variable.

EFA was developed in the early 20th century by Karl Pearson and Charles Spearman. The aims of EFA are to indicate variable that are unobserved or cannot be estimated directly, and to reduce the number of observed variables. The EFA describes the covariance among many variables in terms of a few unobserved variables (Washington *et al*., 2011). Factor analysis is calculated by expressing the X_i'which in a linear function form, such that,

$$\begin{aligned} X_1 - \mu_1 &= \ell_{11}F_1 + \ell_{12}F_2 + \cdots + \ell_{1m}F_m + \varepsilon_1 \\ X_2 - \mu_2 &= \ell_{21}F_1 + \ell_{22}F_2 + \cdots + \ell_{2m}F_m + \varepsilon_2 \\ \vdots \quad & \qquad \vdots \qquad\qquad \ddots \qquad\qquad \vdots \\ X_p - \mu_p &= \ell_{p1}F_1 + \ell_{p2}F_2 + \cdots + \ell_{pm}F_m + \varepsilon_p \end{aligned} \tag{1}$$

In a matrix notation, the factor analysis model will become:

$$(\mathrm{X}-\mu)_{p\times 1} = \mathrm{L}_{\mathrm{p}\times\mathrm{m}} F_{m\times 1} + \varepsilon_{p\times 1} \qquad (2)$$

where F's are factors or variables, and ℓ's are the factor loadings. The ε is associated only with X_i' and, the p are random errors and m factor loading are unobserved or latent variables. The factor rotation method used determines the loading factor. If the loading factor is close to one, this means variable X_i is largely influenced by F_i (Washington *et al.*, 2011).

The results of EFA are ℓ's (loading factor) from Equation (1), shown in Table 3, consisted of 5 components beginning from the consideration of the variables indicating *rear-end crash size* which was found in the second component with a loading factor of *fatality*, *serious injury* and *slight injury* at 0.369, 0.168, and 0.302 respectively. In first component was call driver factor, including *V1-V9* with a loading factor of -0.323-0.881. In third component, it was called road factor consisted of ten variables including V10-V19 with loading factors of -0.744-0.774, respectively. Regarding the forth component, it was called environmental factor which consisted of four variables with loading factor -0.869-0.981. The rear-end collision factors was in the fifth component and consisted of *going straight* and *stopped in road (V24-V25)* with loading factor of 0.935 and -0.633, respectively.

In the analysis, neither factors nor the variable was invented by researchers, but taken from previous local and international research. Based on EFA result, independent variables included road factors, environmental factors, driver factors, and type of crash factors. The continuous factor examined was the number of injuries to drivers and passengers. For the measurement model, a dummy variable was used for the SEM analysis due to the variable group.

Data were used to create a correlation matrix examine to what extent a mutual relationship exists between observed variables. Then SEM was run using the MPlus 7.2 program.

Structural Equation Modeling (SEM)

SEM requires specification of the relationship between observed variables and latent variables. SEMs rely on information contained in the variance-covariance matrix, but latent variables' measurement must distinguish between fixed and free parameters. Fixed parameters are set to a reference variable, which is the base of estimation and comparison with the free parameter, for the structural model is a relationship between independent latent variables and dependent latent variables that have similar linear regression loading factors. Symbols in SEM are of two types: rectangles (meaning observed variable) and circles (meaning latent variable).

Table 3 Standardized loading factor of SEM

Loadings:	Components				
	1	2	3	4	5
V1	**0.337**	0.173	0.303	0.207	−0.226
V2	**−0.176**	−0.129	−0.19	−0.207	0.128
V3	**0.103**	−1.012			
V4	**0.881**				
V5	**0.769**				
V6	**0.22**		−0.169	−0.113	
V7	**−0.323**		−0.110	0.210	
V8	**0.394**		0.139		0.266
V9	**0.174**		0.11		
V10	0.525		**0.277**		
V11	−0.114		**0.725**		
V12			**0.102**		
V13	−0.168		**0.467**		−0.106
V14	0.194		**−0.744**		
V15	−0.195		**0.920**		
V16	−0.109		**0.607**		0.126
V17	−0.167		**−0.207**	-0.178	
V18			**0.774**		
V19			**0.641**		
V20	−0.271			**0.981**	
V21			0.104	**0.273**	
V22	−0.112			**−0.869**	
V23				**0.432**	
V24	0.262		0.283	0.209	**0.935**
V25				0.132	**−0.633**
V26		**0.369**		0.159	−0.138
V27		**0.168**			
V28		**0.302**			

Note: Calling: component 1 = Driver factor, component 2 = crash size, component 3 = Road factors, component 4 = Environmental factor and component 5 = Crash type factor. The rotation = 'Varimax'.

The SEM estimation parameter is similar to that of other statistical models. SEMs are used to evaluate theories or hypotheses using empirical data, which are contained in a *PxP* variance-covariance matrix S, an unstructured estimator of the population variance-covariance matrix Σ (Washington *et al.*, 2011). $\Sigma(\theta)$ is a variance-covariance matrix which turns from a generated model-implied and uses an estimated parameter vector θ. A dependent variable (exogenous variable) in SEM is a variable that has a one-way arrow pointing to it. The set of dependent variables is collected into a vector η, For independent variables (endogenous variables) are collected in the vector ξ. The relationship between them is the following:

$$\eta = \beta\eta + \gamma\xi + \varepsilon \qquad (3)$$

where β is the estimated vector of coefficients that contains regression coefficients for the dependent variable and γ for the independent variable. ε is the vector of regression error terms. The estimator in SEM depends on the distribution assumption of variables and the scale of a variable. This study's scale variables are only discrete data not abnormally distributed. Lee *et al.* (2008) suggested that weighted least squares (WLS) methods estimate rather than assume the multivariate normality of variables.

For model goodness-of-fit Measure (GOF), the first part was basic GOF consisting of Chi-square statistic (χ^2) that presented the difference of covariance matrices among empirical data. Degree of freedom (DF) is the amount of mathematical information available to estimate model parameters. The root mean squared error of approximation (RMSEA) was a fairly correct calculation and showed more accurate statistical examples of χ^2. The value of RMSEA must be less than 0.05 (Hair *et al.*, 2010; Shi *et al.*, 2011; Kline, 2015; Champahom *et al.*, 2020a). The Tucker-Lewis Index (TLI) and the comparative fit index (CFI) illustrate the proportion of difference of χ^2. TLI and CFI varied in that it is actually a comparison of the normed chi-square values for the null and specified model. The value of TLI and CFI ranges from 0 and 1 and appropriate values must be greater than 0.90 (Yu, 2002; Hamdar and Schorr, 2013; Hassan and Abdel-Aty, 2013). To assess GOF, the error of WLS prediction must be considered. Appropriate values of weighted root mean square residual (WRMR) suggested by Yu (2002) must be less than 1.

Table 4. Descriptive statistics

		Descriptive statistics			Average (person)		
Group	**Code**	**Categories**	**Frequency**	**Percentage**	**Slight injury**	**Serious injury**	**Fatality**
Driver Factors	V1	1	3,536	85.56	1.63	0.47	0.58
		0	597	14.44	1.29	0.43	0.30
	V2	1	3,403	82.34	1.20	0.39	0.23
		0	730	17.66	1.37	0.45	0.36
	V3	1	1,055	25.53	1.45	0.41	0.31
		0	3,078	74.47	1.31	0.45	0.35
	V4	1	1,556	37.65	1.35	0.39	0.35
		0	2,577	62.35	1.33	0.46	0.33
	V5	1	707	17.11	1.32	0.44	0.33
		0	3,426	82.89	1.35	0.44	0.36
	V6	1	1,525	36.90	1.34	0.49	0.21
		0	2,608	63.10	1.35	0.41	0.41
	V7	1	49	1.19	0.73	0.73	0.69
		0	4,084	98.81	1.35	0.43	0.33
	V8	1	2,928	70.84	1.38	0.41	0.32
		0	1,205	29.16	1.24	0.50	0.38
	V9	1	1,901	46.00	1.33	0.43	0.33
		2	1,899	45.95	1.29	0.44	0.33
		3	245	5.93	1.61	0.44	0.35
		4	51	1.23	1.19	0.33	0.53
		5	17	0.41	1.94	0.47	0.54
		6	10	0.24	1.74	0.20	0.20
		7	5	0.12	2.80	0.40	0.20
		8	3	0.07	2.00	0.67	-
		9	2	0.05	4.00	-	-
Road Factors	V11	1	2,638	63.83	1.34	0.37	0.33
		0	1,495	36.17	1.35	0.55	0.35
	V12	1	4,027	97.44	1.35	0.44	0.34
		0	106	2.56	1.18	0.46	0.27
	V13	1	3,646	88.22	1.36	0.45	0.35
		0	487	11.78	1.20	0.35	0.26
	V14	1	265	6.41	1.29	0.38	0.31
		0	3,868	93.59	2.07	1.28	0.71
	V15	1	143	3.46	2.08	1.96	0.31
		0	3,990	96.54	1.32	0.38	0.99
	V16	1	399	9.65	1.51	0.31	0.20
		0	3,734	90.35	1.32	0.45	0.35
	V17	1	753	18.22	1.47	0.43	0.27
		0	3,380	81.78	1.31	0.44	0.35
	V19	1	896	21.68	1.33	0.27	0.22
		0	3,237	78.32	1.34	0.48	0.37
Environmental Factors	V20	1	417	10.09	1.09	0.40	0.58
		0	3,716	89.91	1.37	0.44	0.31
	V21	1	3,816	92.33	1.44	0.60	0.40
		0	317	7.67	1.33	0.42	0.33
	V22	1	2,769	67.00	1.39	0.46	0.29
		0	1,364	33.00	1.25	0.38	0.42
	V23	1	287	6.94	1.48	0.64	0.37
		0	3,846	93.06	1.33	0.42	0.33
Rear-end crash type Factors	V24	1	2,693	65.16	1.46	0.44	0.34
		0	1,440	34.84	1.13	0.42	0.33
	V25	1	227	5.49	0.98	0.31	0.40
		0	3,906	94.51	1.36	0.44	0.33

Remark: average of percentage truck (V10) = 16.7, average of Log AADT (V18) = 10.42.

Results and Discussion

Descriptive Data

The overall view of data, as shown in Table 4, shows the group of variables, the names of variables, the types of variable explanations and percentage of categories, and the mean of slight injuries, serious injuries, and fatalities (dependent variables or endogenous variables). There were 25 independent (four groups) variables. Disguise variables of injuries consisted of the number of fatalities, serious injuries, and slight injuries.

The highest mean for fatalities was found to have been caused by the driver factor, with (V7) drunk drivers involved in the most fatalities, a mean of 0.69 (1.19%). Rear-end collisions with large trucks (V1) showed a mean of 0.58 (85.56%), and drivers aged 36-45 years old (V4) at 0.35 (37.65%). Considering drivers' gender (V2), women had greater risk of fatalities than men, with a mean of 0.36 (17.66%). Road factors revealed that non-sloped roads (V15) had the highest mean of fatalities at 0.99 (96.54%), followed by curved roads at a mean of 0.71 (93.53%).

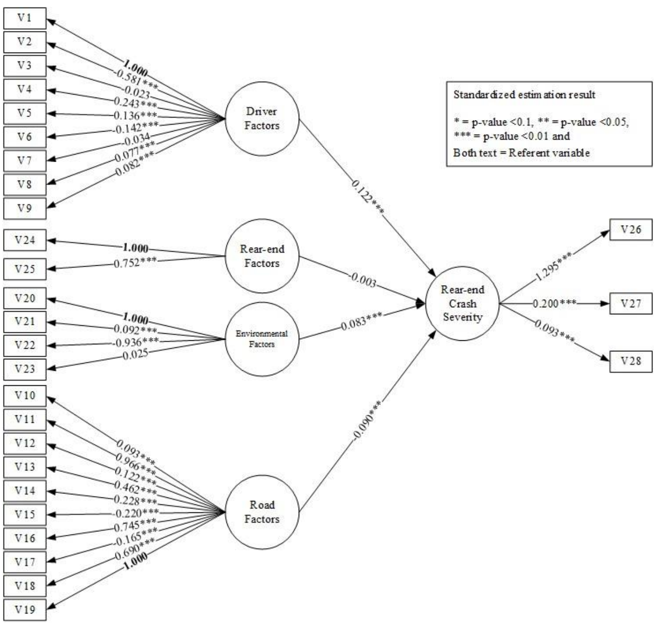
Environmental factors showed rear-end collisions with normal visibility conditions (V21) at 0.4 (92.33%); road with wet surface (V23) at 0.37 (6.94%); accidents occurring during the day (V22) at 0.29 (67%); and accidents occurring without light at night (V20) at 0.58 (10.09%).

Regarding types of rear- end collisions, in which crashes were divided into type of car movement before the crash, the maximum mean of fatalities was with a parked car in front (V25) at 0.4 (5.49%), followed by a leading car slowing down (V24) at 0.34 (65.61%).

For factors affecting serious injuries, road and environmental factors had the highest means at 0.54 and 0.47, respectively, followed by driver factors at a mean of 0.45. Collision factors affecting severity of injuries were in last place with a mean value of 0.44. The highest mean of slight injuries was due to driver factors.

Results of Structural Equation Modeling (SEM)

In analysis of data on rear-end highway collisions, acquired from the Department of Highway (DOH), to determine factors affecting levels of driver and passenger injuries, determined factors were classified into four groups of latent variables including individual, road, environmental, and collision factors. The model was compared with empirical data by considering model fit information values as shown in the note to Figure 1, with a chi-square statistic value = 1,232.160, df = 302 (p-value = 0.000), RMSEA = 0.027, CFI = 0.928, TLI = 0.910 and WRMSR = 1.880. Although WRMSR value was greater than the cutoff value, it could be accepted (Baggio *et al*., 2013; Schnabel *et al*., 2015; Machado *et al*., 2016). Comparison of



Note: Model fit information: Chi-square value (χ^2) = 1232.160, degree of freedom (df) = 302 (p-value = 0.000), Root mean square error of approximation (RMSEA) = 0.027, CFI = 0.928, TLI = 0.910; Weighted root mean square residual (WRMSR) = 1.880.

Figure 1. SEM result model

this model's goodness of fit with cutoff criteria of other research showed it within acceptance criteria; thus, it can be used to interpret research results. Standardized parameters are shown in Table 5.

Table 5. Standardized loading factor of SEM

	Estimate	S.E.	P-value
Measurement Model			
Driver factors			
V1	1	0.000	-
V2	−0.581	0.038	<0.000
V3	−0.023	0.030	0.457
V4	0.243	0.027	<0.000
V5	0.136	0.033	<0.000
V6	−0.142	0.028	<0.000
V7	−0.034	0.069	0.623
V8	0.077	0.029	<0.007
V9	0.082	0.025	<0.001
Road factors			
V10	0.093	0.001	<0.000
V11	0.966	0.019	<0.000
V12	0.122	0.051	<0.000
V13	0.462	0.022	<0.000
V14	0.228	0.032	<0.000
V15	−0.220	0.039	<0.000
V16	0.745	0.019	<0.000
V17	−0.165	0.024	<0.000
V18	0.690	0.010	<0.000
V19	1.000	0.000	-
Environmental factors			
V20	1	0.000	-
V21	0.092	0.035	0.008
V22	−0.936	0.049	<0.000
V23	0.025	0.038	0.461
Rear-end type factors			
V24	1	0.000	-
V25	0.752	0.195	0.001
Accident severity factors			
V26	1.295	0.004	<0.000
V28	0.200	0.008	<0.000
V27	0.093	0.017	<0.000
Structural Model			
Rear-end crash size			
Driver factor	0.122	0.013	<0.000
Environmental factor	0.083	0.009	<0.000
Rear-end type factor	−0.003	0.014	0.820
Road factor	−0.087	0.013	<0.000

Note: Estimate value is standardized

Consideration of the measurement model of rear-end crash severity using three variables including the number of fatalities (reference variable), the number of serious injuries, and slight injuries, found that the number of fatalities from each accident could evidently indicate severity levels of injuries (γ = 1.295, S.E. = 0.004) followed by the number of serious injuries (γ = 0.2, S.E. = 0.008) and the number of minor injuries (γ = 0.099, S.E. = 0.017). Additionally, operational definitions of injury levels were differently distinguished in Thailand and North America. In Thailand, injuries were classified into three levels including death, serious injury, and slight injury, as distributed by levels of hospital treatment. Injury levels in North America were individually divided into the Abbreviated Injury Scale (AIS) by sorting according to body different parts: head, face, neck, thorax, abdomen, spine, upper extremities, lower extremities, and external. Each injury level is assigned an AIS score on an ordinal scale ranging from 1 (minor injury, probability of death = 0%) to 6 (maximum injury, probability of death = 100%) (Stevenson *et al*., 2001). After some consideration, researchers decided that the AIS system's criteria of injury score and duration of treatment in the hospital could not be directly compared. In addition, treatment systems differ to some extent between the two countries.

The structural model revealed that among the four independent latent variables, rear-end collisions' severity was significantly and respectively affected by three factors: driver, road, and environmental. While collision types did not significantly affect severity of injuries, the driver factor most affected injuries' severity (β = 0.122, S.E. = 0.013). In consideration of the measurement model for the *driver factor* providing the reference variable, *large vehicle* (*V1*), which is interpreted as the presence of trucks, the accident would affect the increase of injury severities in accord with studies conducted by Qi *et al*. (2013); Wiacek *et al*. (2015); Piccinini *et al*. (2017). This violent effect may originate from the massive size of trucks causing strike force resulting in more severe injuries. Driver gender was the second variable most affecting levels of injuries, with women receiving more serious injuries possibly because female drivers are hurt more easily than male drivers, conforming to Chen *et al*. (2015) findings that male drivers tended to suffer lower levels of injuries. Another cause may be women's longer stop-car decision time compared to men's (Warshawsky-Livne and Shinar, 2002). For the age factor, drivers were compared by age ranges, including 26-35, 36-45, and 46-55. Drivers 36-55 years old were in more severe accidents, a finding similar to Lee *et al.* (2008), which found that the drivers 40-50 years old affected increasing severity of injuries. Along with safety equipment nonuse, drivers' injury levels increase, following studies of Chen *et al*. (Chen *et al*., 2015; Chen *et al*., 2016b). Other significant factors in causing greater accident severity were the sequential order of involved vehicles and driving over the speed limit.

When considering the *road factors* significantly affecting the levels of injuries (β = -0.09, S.E. = 0.013), overall, every indicator attained statistical significance. The variable with the highest loading factor (reference variable) was the number of traffic lanes (V19). More than four lanes lessened rear-end crashes' severity. This is relevant to a study finding that more traffic lanes potentially decreased fatalities because more lanes caused drivers to be more careful (Chen *et al*., 2016b; Mohamed *et al*., 2017). The divided road variable was determined to compare (V11) rear-end collisions on roads with and without traffic islands. Roads without traffic islands affected levels of injury severity, in accordance with Das and Abdel-Aty (2011) study. According to the main road variable (V16), rear-end collisions occurring on main roads resulted in higher severity. This is relevant to the study of Khorashadi *et al.* (2005) who found that innermost lanes potentially increased injury levels, probably resulting from higher speed on main roads than on parallel roads. Huang, Chin, and Haque (2008), followed by log AADT (V18), found that higher traffic quantity resulted in decreased rear-end crashes, consistent with a study discovering that increased AADT decreased safety (Abdel-Aty and Haleem, 2011; Schorr and Hamdar, 2014). In road surface types (V13), surfaces other than asphalt increased serious injuries in accordance with Lee *et al.* (2008) finding that concrete surfaces affected increasing severity of injuries. For normal roads or work zones (V12), which also affected serious injuries, collisions were caused by drivers exceeding speeds for roads being repaired or maintained (Mohamed *et al.*, 2017). Another variable indicated significantly in the measurement model was collisions at intersections. A leading vehicle's need to brake increased the risk of crash by a following vehicle (Das and Abdel-Aty, 2011). Additionally, a road's grade or slope (V15) created greater severity in rear-end collisions, following Chen *et al*. (2016b). Lower percentages of trucks (V10) affected greater rear-end crash severity. In Thailand, the trucks usually used the arterial roads, there are many traffic lanes. This related to the results of V19, if the number of lanes increased it will be small of rear-end crash size.

As for the environmental factor and significant effects on levels of injuries (β = 0.083, S.E. = 0.009), the measurement model determined darkness (V20) as a reference variable. If an accident occurred at night with no available light, injury levels increased, confirming much research on low visibility leading to more serious injuries (Sullivan and Flannagan, 2003; Yan and Radwan, 2009; Chen *et al.*, 2015; Chen *et al.*, 2016a). Due to reduced traffic at night, drivers who drove at high speed could not stop their cars and crashed into leading cars at low speeds. This was the cause of serious injuries conforming to the variable that compared nighttime and daytime crashes (V22) -nighttime crashes caused greater severity of injury than daytime crashes (Chen *et al*., 2015). For the driver visibility factor, the condition of visibility including clear skies, without dust, fog, or smoke to hinder vision, affected greater severity of injuries (Abdel Aty and Abdelwahab, 2004). The road surface variable was not significant in this measurement model (Chen *et al.*, 2015).

Conclusions

This research studied factors affecting rear-end crash severity on Thailand's highways, as indicated by numbers of fatalities and serious and slight injuries as analyzed with SEM. From analysis of data obtained from the Department of Highway (DOH), these research results can assist organizations involved in law enforcement, including inspectors' offices and organizations involved in road design and maintenance, for instance, the Department of Highways or the Department of Rural Roads, in reducing rear-end crash severity.

The first group of factors increasing rear-end crashes' severity the most is the driver factor: trucks involved, female drivers, drivers from 36-55 years old (at which ages Thai drivers often drive at high speed), not using safety equipment, rear-end crashes caused by driving over the speed limit, the high number of traffic violators in Thailand, and the sequential order of involvement in rear-end crashes. Thus, involved organizations should implement policy to reduce injury severity in rear-end collisions by establishing "Truck Only Lanes" (Chrysler, 2016) that can reduce conflicts between trucks and other drivers. Another policy for female drivers' safety is using the "two dots" or "tailgating" indicator, now available only on Thai motorways, to warn drivers about leaving space behind lead vehicles. This installation would benefit both males and females, of course (Hutchinson, 2008).

The second group of factors concerns roads, which affect rear-end crash severity due to the number of traffic lanes, traffic islands, main roads, road surface types, intersections, road steepness, road bends, and roads in maintenance. Policy from this variable group involves Road Safety Audits, especially, four- or fewer than four-lane roads and roads without traffic islands that decrease rear-end crash severity.

The last group of factors affecting rear-end accident severity is environmental. Indicators causing rear-end crash severity are roads without light at night and clear visibility, which seems to encourage speeding. For potential policy, light installations in risky areas, for instance, truck-parking areas, should be considered. Another potentially useful policy measure is effective speed-limit enforcement. Technology might assist here, with installation of speed-censoring cameras.

Applications of this research in other developed countries might involve differences among the three main factors of driver, road, and environment. The road factor can be directly applied, for instance, by performing Road Safety

Audits. The environmental factor can be instantly applied, for instance, light improvement to reduce rear-end collision severity, and “Truck Only Lanes” can be considered for immediate installation. However, some conditions, for example, AADT, and truck percentage, may differ from those in Thailand. As for speed limits and safety equipment use, compulsory enforcement was potentially more successful in more highly developed countries.

This study found factors affecting rear-end collision severity and introduced guidelines for its reduction. However, the study contains model limitations due to unanalyzed passenger characteristics. Those variables potentially result in increasing severity of rear-end collisions, which might result from data collection limitations, that is, not including passenger characteristics: the number in each vehicle, their use of safety equipment, and their gender. Thus, these factors are proposed for additional, future study.

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