International Journal of Technology 14(6) 1216-1227 (2023)
Received June 2023 / Revised September 2023 / Accepted September 2023

International Journal of Technology

http://ijtech.eng.ui.ac.id

Structural Equation Modeling of Right-Turn Motorists at Unsignalized Intersections: Road Safety Perspectives

Fajaruddin Mustakim[1], Azlan Abdul Aziz[1*], Azwan Mahmud[2], Saifulnizan Jamian[3], Nur Asyiqin Amir Hamzah[1], Nor Hidayati Binti Abdul Aziz[1]

[1]*Faculty of Engineering and Technology, Malaysia Multimedia Uni., 75450 Ayer Keroh, Melaka*
[2]*Faculty of Engineering, Malaysia Multimedia Uni., 63100 Cyberjaya, Selangor*
[3]*Faculty of Mechanical and Manufacturing Eng., Univ. Tun Hussein Onn Malaysia, 86400 Batu Pahat, Johor*

Abstract. This study aims to determine traffic behavior at the selected unsignalized intersection and the development of right-turn motorists (RTM) by adopting the logistic regression method (LRM) and structural equation modelling (SEM). In the early stage of the study, we analyzed the traffic behavior focusing on traffic volume and turning volume at the field site. This study involves five unsignalized intersections (UI), and it observes three types of turning volume: right turn volume (RTV) from a minor road onto a major road, left turn volume (LTV) from a minor road onto a major road, and right turn volume (RTV) from a major road onto a minor road. Although the SEM approach is among the popular scientific analysis and wisely applied in various fields of study, there is less attention to traffic behavior and road safety. An SEM model was developed for right-turn motorists using 812 datasets was developed, and variables that influenced the decision of right-turn motorists (RTM) were identified. Among the six variables analyzed in this statistical model, we identified gap, motorcycle rider, conflict lane change, and the traffic signal to be significant.

Keywords: Logistic regression method; Structural equation modeling; Traffic behavior

1. Introduction

Trafic safety and management has attracted many researchers to conduct various studies and analysis for improved safety and efficiency (Trapsilawati *et al.*, 2023; Siregar *et al.*, 2022; Sumaryo *et al.*, 2019). Unsignalized intersections play a crucial role in the transportation network, and understanding the traffic flow and behavior at these intersections is essential for effective traffic management and planning. Among the various movements at these intersections, right turns pose unique challenges and safety concerns. Understanding the factors that influence the behavior of right-turn motorists is essential for developing effective road safety strategies. Researchers have developed many methods to address this issue in decades, and one popular method is based on statistical methods.

Another popular approach is Structural Equation Modelling (SEM), which is also a statistical method used to model complex relationships between observed and unobserved (latent) variables. SEM is interpreted as a multiple regression equation, estimating a group of datasets interdependently and simultaneously by using a structural model (Hair *et al.*, 2006). Equation 1, defines the relationship between an observed and unobserved variable:

*Corresponding author's email: azlan.abdaziz@mmu.edu.my, Tel.: +60-09-2523322;
doi: 10.14716/ijtech.v14i6.6644

$$x = l.Y + e \tag{1}$$

Where x is the observed variable, the loading l is a regression coefficient measuring connectivity between x and Y, and e represents random measurement error.

Analysis of Moment Structures (AMOS), which is introduced by IBM Corporation (Arbuckle, 2013) and the Structural Equation Program (EQS) provides SEM analysis using visualization and syntax techniques. Besides dataset analysis, this software can present over 20 model fit indexes to test and validate the model (McQuitty and Wolf, 2013).

Structural Equation Modeling (SEM) has been widely used in research studies to incorporate crash severity-related features, such as the number of injured and deceased individuals, as well as the number of vehicles involved. These features are combined into a latent construct known as "crash size," which offers a comprehensive and more dependable measure of actual crash severity (Lee, Chung, and Son, 2008). Additionally, the concept of a 'crash risk' latent variable has been introduced, combining surrogate safety measures and crash data to model specific crash types that occur infrequently (Yang *et al.*, 2021). Moreover, SEM's capability to model indirect effects has gained attention in naturalistic driving studies and real-time crash prediction models, allowing for the consideration of complex associations among intercorrelated variables (Xu *et al.*, 2018). Another statistical approach called Generalized SEM (GSEM) has been developed by Hyun *et al.* (2021) to address the limitations of traditional SEM when analyzing safety data. Traditional SEM assumes that the variable of interest follows a normal and non-continuous distribution (Grace *et al.*, 2012), which may not hold true for safety data. GSEM combines the strengths of SEM and Generalized Linear Models (GLM) to create a more flexible modeling framework. By incorporating GLM techniques, GSEM allows researchers to appropriately analyze safety data with non-normal or non-continuous distributions. Gharraie and Sacchi (2021) applied SEM with generalized (ordered probit) links to investigate the severity of wildlife-vehicle crashes in Canada, considering the discrete and ordinal nature of the response variable. Similarly, Kim, Pant, and Yamashita (2011) employed SEMs in a Bayesian framework to explore crash severity in relation to various factors, utilizing the flexibility of the Bayesian approach to model both continuous and discrete variables, thereby incorporating ordinal and continuous random variables in their analysis. These studies highlight the effectiveness of SEM in analyzing crash severity and associated factors while considering the specific characteristics of the data.

By using regression and logistic regression approach, (Fajaruddin. Fujita, and Wisetjindawat, 2013) analyzed accident causality and traffic behavior at black spot locations on Malaysia Federal Route. The study revealed that the most unsafe turning maneuver is the movement of a right-turning motorcycle from a minor to a major road and a left-turning motorcycle from a minor road. (Fajaruddin *et al.*, 2021) have developed rider and passenger car models by applying binary regression. However, it does not concentrate on traffic volume, turning behavior, and implementation of structural equation modeling. (Fajaruddin *et al.*, 2021: Fajaruddin. Fujita, and Wisetjindawat, 2013), have established for the right-turning motorist and clearly described a gap sequence at unsignalized intersections. Sevenster *et al.* (2023) investigates response time in driver overtaking decisions by using a driving simulator experiment. The study discovered that the response time for accepted gaps was shorter than for rejected gaps. This scenario occurred when the response time for the accepted gap decreased depending on the early velocity of the ego motorist. Conscience, the response time increased with the distance gap. The decision to overtake a motorist with oncoming traffic can be a critical and risky maneuver. Observation and estimation of the gap can be defined as a gap acceptance decision, and it is one of the crucial processes. In this circumstance, if the driver misjudges the gap oncoming motorists on the major road, it could be exposed to a hazardous situation (Branzi *et al.*, 2021). Recently, Zgonnikov *et al.* (2022) developed a cognitive model (cognitive processes programming) that analysis gap acceptance decisions in left-turn vehicles at intersections. The result found that in the situation of time pressure, the driver needs to make the decision quickly before the oncoming vehicles is too close.

The previous studies obviously lack attention to traffic behavior and road safety. Therefore, in this study, we develop an SEM model which provides a comprehensive understanding of the behavior of right-turn motorists at unsignalized intersections from a road safety perspective using a Malaysia case study. Our aim is to identify the variables that significantly influence the decision-making process of right-turn motorists and their impact on road safety. The study utilizes structural equation modeling (SEM) to analyze the behavior of right-turn motorists. A dataset consisting of 812 observations is collected. The researchers developed an SEM model to examine the relationships between variables, considering factors such as the gap, presence of motorcycle riders, conflict lane change, and the presence of a traffic signal. A comparative study will be presented against a widely popular statistical approach based on the logistic regression method (LRM). With LRM, early preparation of selection variables in the model can be developed for the SEM analysis. From this study, we determined that variables such as gap, motorcycle rider, conflict lane change, and the traffic signal significantly influence road safety.

This paper is organized as follows: Section 1 is the introduction, Section 2 provides the methodology of the study, the development of LRM is given in Section 3, the development of SEM in Section 4, a brief discussion is in Section 5, and followed by the conclusion in Section 6.

2. Methodology

2.1. SEM Fit Index

SEM programming comprises standard error with each calculated loading and related t-test. If the sample size for SEM estimation is larger than 200, the Chi-square value can also be determined, which usually results in high statistical power. Therefore, significant loading is desirable, and even if it is not attained, the model is still meaningful. Typically, the chi-square ($\chi2/df$) statistical ratio recommended ranges as low as 2.0 and up to 5.0 (Tabachnick, Fidell, and Ullman, 2007). The root-mean-square error of approximation (RMSEA) is used as the second fit index in this study. It provides information about how well the model fits the data, considering the number of parameters estimated in the model. If the model provides a good fit to the population covariance matrix, it suggests that the model accurately represents the relationships between the variables in the population. The cut-off values of the RMSEA should be between 0 to 0.08 (McQuitty, 2004). Besides the Chi-Square test, the Goodness of Fit Index (GFI) can be used to measure the quantity of variance in the model by the estimated amount of covariance (Tabachnick, Fidell, and Ullman, 2007). This statistical index ranges from 0 to 1. Adjusted Goodness of Fit Index (AGFI) is a modification of the Goodness of Fit Index (GFI) that considers the degrees of freedom in the model. AGFI is calculated by adjusting GFI for the expected fit under the null hypothesis of a completely saturated model, given the degrees of freedom in the actual model. Like the GFI, the AGFI ranges between 0 and 1, and a value of 0.90 or higher shows a well-fitting model, according to (Tabachnick, Fidell, and Ullman, 2007).

The root mean square residual (RMR) is a measure of the discrepancy between the hypothesized covariance model and the sample residuals of the covariance matrix, and its scale depends on the variables being measured. The Norm Fit Index (NFI) compares the $\chi2$ value of the model with the $\chi2$ value of the null model, which assumes that all tested variables are unrelated and represents the worst-case scenario. This statistical index ranges from 0 to 1. Another interesting model is called the comparative fit index (CFI). It is a reviewed form of the NFI, which concentrates on sample size. The index performs well even though the sample size is smaller (Tabachnick, Fidell, and Ullman, 2007). Like NFI, the value of CFI ranges between 0 and 1. An index value that is close to 1 shows a good fit.

Too many models' fit indexes in SEM create phenomena of reporting results because of complexity, issues, and the acceptable margin of the fit indexes. Describing and evaluating a hypothesized model does not require all fit indices to be included. The choice of the fit index to use typically depends on the purpose of the study, as noted by Alavi *et al.* (2020).

2.2. Model Modification and Fitness

Although SEM involves complex statistical methods, there are software tools available that make it relatively easy to apply. The scientific tool can analyze single and multiple models concurrently and estimate effectively. Modification indices (MI) found under analysis properties in the SEM provide information on modification value. Modifying covariances between variables, whether by expanding the network or removing errors in the measurement model (MI), could enhance the fit of models, including Chi-Square, NFI, RMSEA, RMR, GFI, AGFI, RFI, IFI, CFI, and RMSEA (Arbuckle, 2013; McQuitty and Wolf, 2013; Loehlin, 2004). When attempting to improve the model fit of an SEM, it is important to consider both the theoretical aspects of the model and the fit indices. We should not disregard theoretical considerations in favor of only improving the model fit (Teo, Tsai, and Yang, 2013). Before implementing the model in SEM, this study used the logistic regression method to examine and validate all model parameters carefully to ensure that they align with the theoretical foundation of the model.

2.3. Data Collection

We performed this study on Malaysia's Federal Route 50. It has four lanes of a two-way, partially divided road. The total stretch of the roadway from Batu Pahat to Ayer Hitam is about 40 km. The existing road consists of high-density of access roads or unsignalized intersections. This is because the location of the route crosses several housing areas, industrial hubs, and commercial buildings. In the year 2022, it has a capacity providing approximately 80,102 veh/day and up to 7,949 veh/hr. The design speed for this route is around 100 kph. Meanwhile, the method applied in this study includes site investigation, video recording, traffic behaviour analysis, critical gap, speed study, gap pattern, development of right turn model, and the conflict model. We have implemented binary regression or logistic regression and structural equation modeling in the models.

Video cameras were at selected unsignalized intersections (UI), and data collection was concentrated on all traffic maneuver behavior, as illustrated in Figure 2. Data of vehicles, classified by types, like cars, motorbikes, lorries, and public transport, were gathered from hourly traffic volume (disaggregated according to every type of motor vehicle), occurring on every chosen unsignalized intersection (UI2, UI 8, UI 9, UI 10 and UI 20). All selected UI is in the urban area except UI 20 in the suburban region.

Data on conflict situations, approach speeds, vehicle flow, and pedestrian crossings were simultaneously collected. Once the recording finished, all the video cams were brought to the laboratory for further microscope analysis. The selection of an unsignalized intersection (UI) was based on two aspects: first, the accident's blackspot ranking recorded (Fajaruddin *et al.*, 2021), and second, the road safety facilities provided on that UI. UI 2 was a three-leg unsignalized junction. It has concrete dividers, right-turn channelization, and traffic lights approximately 100 meters from the intersection in the middle of the mainstream road. UI 9 was a three-leg junction and traffic signal located around 100 meters from the intersection. UI 9 didn't equip concrete road median and right turn channelization. Meanwhile, UI 8 and UI 10 were a three-leg junction connecting four lanes on a major road with a two-lane minor road, as illustrated in Figure 1. It has no traffic safety facilities such as traffic signals, concrete road medians, and right-turn channelization. UI 20 is in a suburban area, which has 4 leg unsignalized intersections and four lines on the major road. In this study, five UI are involved in turning volume behavior, and only three UI selected (UI 2, UI 9, and UI 10) focus on right-turning motorist analysis and development of structural equation modeling.

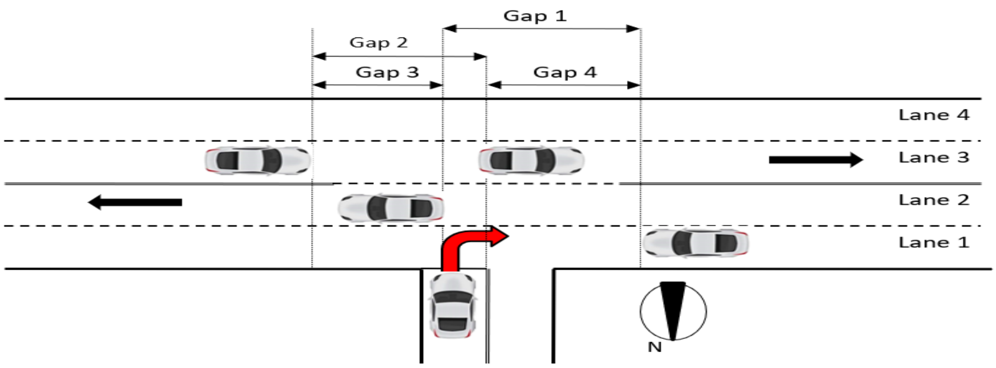

Figure 1 Right turning at a three-leg unsignalized intersection, the four potential gap patterns for motor vehicle acceptance or rejection (UI)

2.4. Traffic Volume

We collected a traffic count at five unsignalized intersections, UI 2, UI 9, UI 10, UI 8, and UI 20, using video cameras. Traffic data conducted in this paper were based on hourly traffic volume and focused on three peak hours, namely morning (8:00-10:00), midday (12:00-14:00), and afternoon (16:00-18:00). Figure 2 illustrates the highest traffic volume was during the afternoon at (17:00-18:00) stated 4,804 veh/hr, 4,500 veh/hr, 4,368 veh/hr, 4,142 veh/hr and 2218 veh/hr for UI 2, UI 8, UI 9, UI20 and UI 10 respectively. The second highest traffic volume was during the morning (8:00-9:00) recorded at 3,887 veh/hr, 3,632 veh/hr, 3,072 veh/hr, 2,760 veh/hr, and 2,707 veh/hr for UI8, UI2, UI 10, UI20 and UI9 respectively. Conscience, the third highest traffic volume was during midday at (13:00-14:00) got 3,628veh/hr, 3,612 veh/hr, 2,822 veh/hr, 2,551 veh/hr and 2,168 veh/hr for UI 20, UI 2, UI 8, UI 9 and UI 10, respectively. Although UI 2 achieved the highest traffic volume during (17:00-18:00= 4804 veh/hr, however in right turning volume from a minor road onto a major UI2 received the lowest (17:00-18:00= 34veh/hr).

2.5. Right Turn Volume from Minor Road

Right turning volume in this section is defined as right turn motorist from a minor road onto a major road at the selected intersection (Figure 2). Five unsignalized intersections (UI) were involved in right turn volume analysis, which are UI 2, UI 8, UI 9, UI 10, and UI 20. As mentioned before in the previous section, the traffic count was based on hourly traffic turning volume (veh/hr) at three peak hours (8:00-10:00), (12:00-14:00) and (16:00-18:00). Figure 3 shows turning volume over six hours' duration. Right turning flow at UI 10 recorded in uniform trend in early stage recorded (8:00-9:00 = 41 veh/hr), (9:00-10:00 = 39 veh/hr), (12:00-13:00 = 44 veh/hr), (13:00-14:00 = 55 veh/hr), (16:00-17:00 = 42 veh/hr) but drastically increase at (17:00-18:00 = 244 veh/hr). Other turning flows at UI 2, UI 8, UI 9, and UI 20 represent a stable turning maneuver and less fluctuation with a minimum range of 34 veh/hr and a maximum of 92 veh/hr, compared with UI 10.

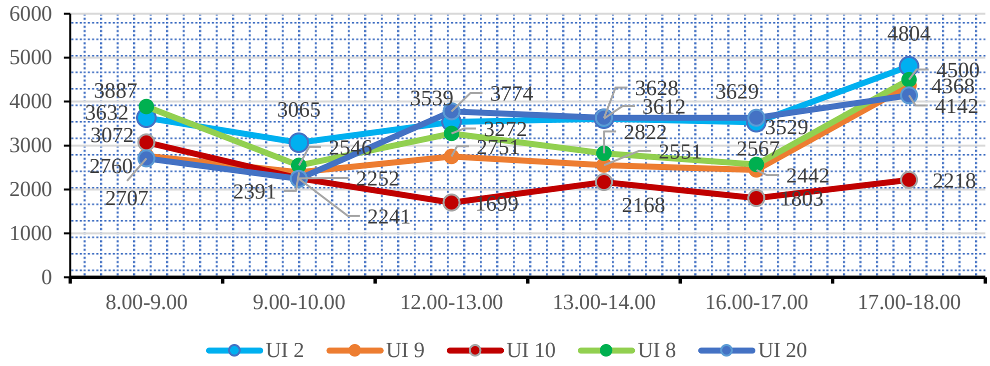

Figure 2 Traffic volume from minor road fluctuation over six hours survey during a typical weekday

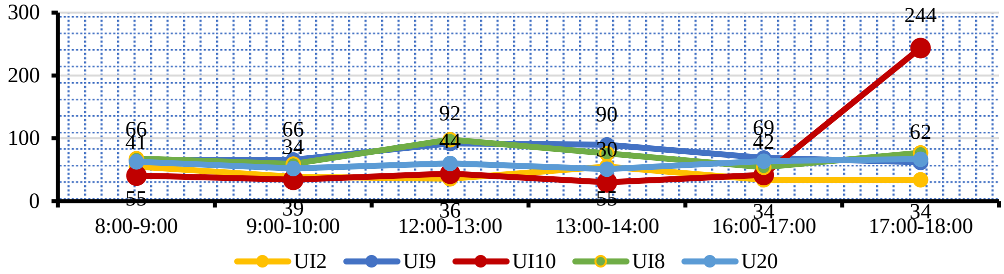

Figure 3 Right turning volume from minor road fluctuation over six hours survey during a typical weekday

2.6. Left Turning Volume from Minor Road

Left turning volume in this section is defined as a left turn motorist from a minor road onto a major road at the selected intersection. Figure 4 shows the turning volume over six hours' duration. Left turning volume at UI 9 recorded in less fluctuation trend in morning and midday, was (8:00-9:00 = 89 veh/hr), (9:00-10:00 = 65 veh/hr), (12:00-13:00 = 78 veh/hr), (13:00-14:00 = 67 veh/hr), (16:00-17:00 = 97 veh/hr) however sharply rise during the afternoon (17:00-18:00 = 213 veh/hr). Meanwhile, UI 10 has a different situation pattern during midday (12:00-13:00 = 115veh/hr), achieving the highest left-turning volume and second highest during the afternoon (17:00-18:00= 184 veh/hr). Subsequently, other turning volumes at UI 2, UI 8, and UI 20 represent a uniform turning maneuver and less fluctuation with a minimum range of 8 veh/hr and a maximum of 63 veh/hr.

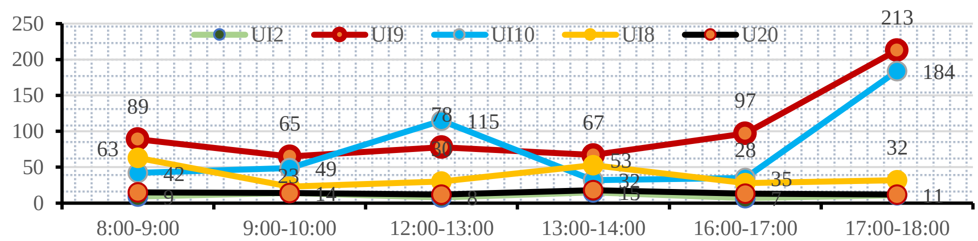

Figure 4 Left turning volume from minor road fluctuation over six hours survey during a typical weekday

2.7. Right Turn Volume from Major Road (RTVmr)

Right turning volume from a major road in this section is defined as the right turn motorist from a major road onto a minor road at the selected intersection. Figure 5 shows the turning volume over six hours' duration. Right turn volume from the major road has a different turning pattern compared with other right turning volumes from the minor road (Figure 3) and left turning volume from the minor road (Figure 4). Concisely, the right turning volume at UI 8 in the morning was (8:00-9:00 = 70 veh/hr) and the number of traffic plumped (9:00-10:00 = 40 veh/hr). Meanwhile, the volume rises drastically at 121 veh/hr and 123 veh/hr during midday (12:00-13:00) and (13:00-14:00) respectively. However, the volume dropped suddenly with 46 veh/hr in the afternoon (16:00-17:00) and increase doubled to 83 veh/hr at (17:00-18:00). Briefly, UI 20 demonstrate active variation volume flow from morning stated (8:00-9:00 = 46 veh/hr) drop at (9:00-10:00 = 26 veh/hr) sharply rise in midday (12:00-13:00 = 58 veh/hr) and (13:00-14:00 = 95 veh/hr), slightly reduce in the afternoon (16:00-17:00 = 86 veh/hr) before rocketed (17:00-18:00 = 111 veh/hr).

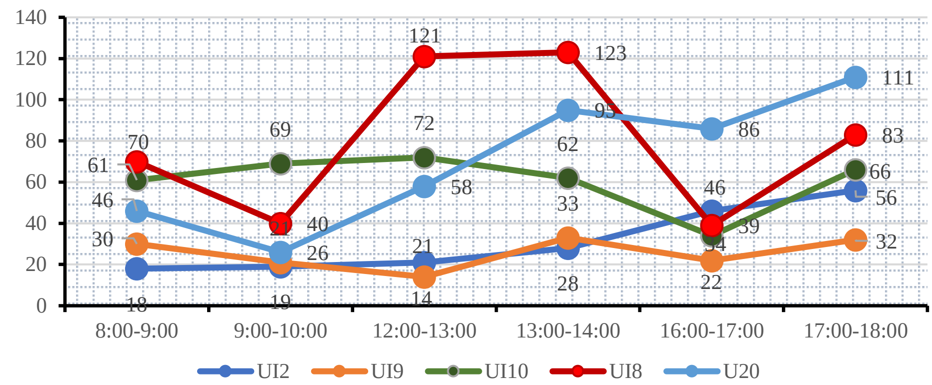

Figure 5 Right turning volume from major road fluctuation over six hours survey during a typical weekday

UI 2 turning volume performed a gradually increasing trend from early morning (8:00-9:00=18 veh/hr) and (9:00-10:00= 19 veh/hr), continuing during midday (12:00-13:00 = 21 veh/hr) and (13:00-14:00= 28 veh/hr), slightly rise during the afternoon was (16:00-17:00 = 46 veh/hr) and (17:00-18:00 = 56 veh/hr). UI 10 maneuver volume trend represents uniform flow in the morning and afternoon recorded (8:00-9:00 = 61 veh/hr, 9:00-10:00 = 69 veh/hr, 12:00-13:00 = 72 veh/hr, 13:00-14:00 = 62 veh/hr), drop slightly in the afternoon (16:00-17:00 = 34 veh/hr) and finally increase (17:00-18:00 = 66 veh/hr). Meanwhile, UI9 turning flow has less traffic volume and fluctuation between 14 veh/hr and 33 veh/hr.

3. Development of Logistic Regression

812 data points for Right-Turning Motorists (RTM) comprised 351 accepted gaps, and 461 rejected gaps utilized in the development of the RTM Models. Subsequently, gap, motorcycle rider, conflict lane change (CLC), channelization, and traffic signal were set as independent variables or predictors. Meanwhile, the dependent variable in logistic regression was RTM and set to 1 and 0 if otherwise. Validation of the model was done with SPSS Statistics 26. The significant intervals of 90%, 95%, and 99% were determined using a stepwise selection procedure. The description of all dependent and independent variables is explained in Table 1, and the RTM Models for Right Turn Motorists in Table 2.

Table 1 Attributes of traffic behavior models

Abbr.	Description
RTM	RTM=1 if the motorist turned right at a gap, but 0 if not.
Gap	Gap which is rejected or accepted (sec).
Car	Car=1 if the RTM is a car, and 0 if otherwise.
Mc	Mc=1 if the RTM is a motorcycle, and 0 if otherwise.
Rider	Rider= 1 if the RTM is rider, and 0 if otherwise.
Van	Van= 1 if the RTM is van, and 0 if otherwise.
Lorry	Lorry= 1 if the RTM is lorry, and 0 if otherwise.
Bus	Bus= 1 if the RTM is a bus, and 0 if otherwise.
CLC	Conflict lane change = 1 if CLC occurred and 0 if otherwise.
Gap1	If the gap was gap pattern 1 in Figure 4, Gap1=1, but 0 if not.
Gap2	If the gap was gap pattern 2 in Figure 4, Gap2=1, but 0 if not.
Gap3	If the gap was gap pattern 3 in Figure 4, Gap3=1, but 0 if not.
Gap4	If the gap was gap pattern 4 in Figure 4, Gap4=1, but 0 if not.
Gap5	If the gap was gap pattern 5 in Figure 5, Gap5=1, but 0 if not.
Chanlz	If the channelization facility is in an unsignalized intersection, so Chanlz = 1, but 0 if not.
TSignal	If all vehicles are in an unsignalized intersection, so TSignal=1, but 0 if not.

In Model 1, three variable, which is vehicle gap, conflict lane change (CLC), and traffic signal, achieved significance at a 99% level, followed by rider received 95% significance, and channelization stated a 90% significance level.

Table 2 Logistic Regression Models for Right Turn Motorists (RTMs)

Attributes	Model 1
	All (detail)
Constant	-5.35(187.29)***
Gap	0.96(201.97)***
CLC	4.18(28.95)***
Rider	0.59(5.73)**
TSignal	-0.67(6.36)***
Chanlz	-0.83(3.04)*
N	812
NagelkerkeR^2	0.72
H.R-Right Turn	83%
H.R-Total	87%

*,**,***=Significant at 90%,95%, and 99% levels, respectively

In RTM logistic model 1, a positive sign of rider and serious conflict lane change shows that RTM is likely to accept a shorter gap acceptance. Conversely, a negative sign in the traffic signal and channelization can be interpreted to mean that RTM is likely to accept a longer gap.

4. Development of SEM

The dataset applied in the right-turning motorist (RTM) behavior model for logistic regression is the same dataset implemented in structural equation modeling. The relationship between exogenous and endogenous latent variables can be visualized through the SEM diagram. In addition, SEM's ability to assess both causal impact among these observed and unobserved variables. In this model, endogenous variables were RTM and six exogenous variables (rider, gap, conflict lane change, channelization, and traffic signal).

The IBM SPSS AMOS 23 computer programming is used to develop structural equation modeling (SEM). AMOS 23 (Arbuckle, 2013), is a software for analyzing, validating, and testing observed data. Meanwhile, SPSS 26 is used to prepare the dataset. Table 3 shows the outcome results for each variable in the analysis.

Table 3 Result of SEM for Traffic Behaviour

			Estimate	S.E.	C.R.	P	Label
RTM	<---	CLC	.573	.063	9.168	***	par_5
RTM	<---	Gap	.080	.003	25.540	***	par_6
RTM	<---	Tsignal	-.080	.029	-2.764	***	par_7
RTM	<---	Chlzation	-.041	.045	-.926	.354	par_10
RTM	<---	Rider	.066	.028	2.394	.017	par_11

*,**,***=Significant at 90%,95%, and 99% levels, respectively

The details, such as parameter estimate, standard error (S. E), critical ratio (C. R), and level of statistical significance (P), are described in Table 3. All four variables, namely gap acceptance (Gap), traffic signal (TSignal), and conflict lane change (CLC), were highly statistically significant statistically at 99%, excluding motorcycle riders got a 95% significance level. Meanwhile, channelization was found insignificant. Each parameter shows a positive sign, except traffic signal and channelization get a negative sign. The positive sign of conflict lane change, gap, and motorcycle rider shows RTM is likely to accept a short gap. Subsequently, the negative sign of the traffic signal shows the RTM is likely to accept a longer gap. The Chi-square $\chi 2$ was 9.445. Meanwhile, the $\chi 2/df$ statistic index was 3.145, which is less than 5.0, showing a good fit of the model (Schumacker and Lomax, 2004). The root mean square residual (RMR) index has a value of 0.010. The index of (RMR) less than 0.08 means the index is quite good (Benitez *et al.*, 2020). Subsequently, the root mean squared error of approximation (RMSEA) is 0.05, which is less than 0.05. A value equal to or less than 0.05 usually shows the good quality of the model, and when RMSEA is between 0.07-0.09, the model is in categories of logical estimation. (Khassawneh, Mohammad, and Ben-Abdallah, 2022). The goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI) had values of 0.996 and 0.973, respectively. The index was close to 1.0, showing a perfect fit for the conflict model (Hair *et al.*, 2010). The comparative fit index (CFI), tucker-lewis coefficient (TLI), and normal fit index (NFI) were 0.996, 0.949, and 0.985, respectively. All Incremental Fit Indexes are close to 1.0, representing the best fit of the model (Benitez, Ray, and Henseler, 2018). We concluded that the fit of our model is excellent and sufficient to proceed. The summary of the model index value and its requirement is shown in Table 4.

Table 4 Goodness-of-fit indexes

Indexes Values	Values	Requirement
Chi-Square	9.45	Significance > 0.05
$\chi 2/df$	3.15	Between 2-5 (Tabachnick, Fidell, and Ullman, 2007)
Goodness of Fit Index (GFI)	0.99	
Adjusted Goodness of Fit Index (AGFI)	0.97	close to 1, (Hair *et al.*, 2010)
Comparative Fit Index (CFI)	0.99	close to 1, (Hair *et al.*, 2010)
Tucker-Lewis Coefficient Index (TLI)	0.95	> 0.90, (Benitez, Ray, and Henseler, 2018)
Normal Fit Index (NFI)	0.99	> 0.90, (Benitez, Ray, and Henseler, 2018)
Relative Fit Index (RFI)	0.93	> 0.90, (Benitez, Ray, and Henseler, 2018)
Incremental Fix Index (IFI)	0.99	> 0.90, (Benitez, Ray, and Henseler, 2018)
Root Mean square Residual (RMR)	0.01	> 0.90, (Benitez, Ray, and Henseler, 2018)
Root Mean Square Error of Approximation (RMSEA)	0.05	< 0.08 (Benitez *et al.*, 2020) < 0.08 (Khassawneh, Mohammad, and Ben-Abdallah, 2022)

The root mean squared error of the approximation calculation formula is defined by Equation 2.

$$RMSEA = \sqrt{\frac{(\chi^2 - df)}{df(N-1)}} \tag{2}$$

Where N number of observations (812), df the degrees of freedom (3), and Chi-square $\chi 2$ of the model (9.45).

5. Discussion

At the early stages, using SEM can be challenging as researchers need a basic understanding of statistical analysis, model fit indices, variable networks, and the connections between endogenous and exogenous variables, as well as observed and unobserved (latent) quantitative variables. However, as one gains experience and regularly practices developing structural models with proper guidance, it becomes more engaging. This is especially true when leveraging modification indices (MI) to fine-tune the model, such as increasing covariance between independent variables based on MI suggestions, leading to improved model fit indices.

The resulting outcome from both scientific methods (SEM and LRM) revealed similarity independent variables such as gap, traffic signal and conflict lane change, acquiring a significance level at 99%. Only the RTM motorcycle achieved a 95% confidence level. The same -/+ sign of each variable is given in both methods. Despite the independent variable of channelization insignificance in structural equation modeling, these parameters have statistical significance at 90% in the logistic regression model. All ten goodness-of-fit indices support the analysis having more accuracy in the SEM. SEM can present a visualization modeling network. Meanwhile, LRM has the advantage of assisting in explaining the result and early preparation of selection variables in the model before execution of the SEM. Thus, a combination of both scientific and statistical might complement each other and create essential understanding in our research work. The results of the SEM analysis provide a comprehensive understanding of the behavior of right-turn motorists at unsignalized intersections from a road safety perspective.

6. Conclusions

The study identifies significant variables that influence the decision-making process, highlighting their impact on road safety considerations. These findings contribute to the development of effective road safety measures and interventions for unsignalized intersections. Furthermore, the findings could serve as basic research for road safety design, autonomous vehicle as well as vehicle-to-vehicle communication, specifically employing artificial intelligence methods. Besides that, this study has the potential to extend another three-turning behavior at unsignalized intersections, such as a left turn from a minor road to a major road, a right turn from a major road to a minor road, and a left turn from a major road to minor road. Moreover, the researcher has intention to explore the Internet of Vehicle (IoV), vehicle-to-vehicle communication (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X) in traffic behavior study for the next future research work. Future studies may address issues in information sharing in the heterogenous vehicular networks about traffic conditions such as traffic congestion, accidents with each other and with traffic controller systems. This will enable more efficient traffic flow and fully autonomous vehicles.

Acknowledgments

This work was supported by the Ministry of Higher Education, Malaysia FRGS/1/2019/TK08/MMU/03/1 and TMRND Grant MMUE/190012.

References

Alavi, M., Visentin, D.C., Thapa, D.K., Hunt, G.E., Watson R., Cleary, M., 2020. Chi-Square for Model Fit in Confirmatory Factor Analysis. *Journal Advance Nursing,* Volume 76(9), pp. 2209–2211

Arbuckle, J.L., 2013. *Amos 22 User Guide.* USA: Amos Development Corporation

Benitez, J., Henseler, J., Castillo, A., Schuberth, F., 2020. How To Perform And Report An Impactful Analysis Using Partial Least Squares: Guidelines for Confirmatory and Explanatory IS Research. *Information and Management*, Volume 57, p. 103168

Benitez, J., Ray, G., Henseler, J., 2018. Impact of Information Technology Infrastructure Flexibility on Mergers and Acquisitions. *MIS Quarterly*: *Management Information Systems*, Volume 42(1), pp. 25–43

Branzi, V., Meocci, M., Domenichini, L., Calcinai, M., 2021. A Combined Simulation Approach to Evaluate Overtaking Behaviour on Two-Lane Two-Way Rural Roads. *Journal of Advanced Transportation,* Volume 2021, pp. 1–18

Fajaruddin, M., Aziz, A.A., Fujita, M., Wisetjindawat, W., Ahmad, M.N., Sukor, N.S.A., 2021. An Analysis of Right-Turning Vehicles and Gap Acceptance Behaviour Models on Malaysian Rural Roads. *International Journal of Road Safety*, Volume 2(1), pp. 45–53

Fajaruddin, M., Fujita, M., Wisetjindawat, W., 2013. Analysis of Fatal-Serious Accidents and Dangerous Vehicle Movements at Access Points on Malaysian Rural Federal Roads. *Journal of Japan Society of Civil Engineers,* Volume 69(4), pp. 286–299

Gharraie, I., Sacchi, E., 2021. Severity Analysis of Wildlife–Vehicle Crashes Using Generalized Structural Equation Modeling. *Transportation Research Record*, Volume 2675(2), pp. 53–64

Grace, J.B., Schoolmaster, D.R.Jr., Guntenspergen, G.R., Little, A.M., Mitchell, B.R., Miller, K.M., Schweiger, E.W., 2012. Guidelines for a Graph-Theoretic Implementation of Structural Equation Modeling. *Ecosphere,* Volume 3(8), pp. 1–44.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2010. Multivariate Data Analysis. 7th Edition. Englewood Cliffs: Prentice Hall

Hair, J.F., Jr., Black, W.C., Babin, B.J., Anderson, R.E., Tatham, R.L., 2006. *Multivariate Data Analysis*. 6th Edition. Upper Saddle River, NJ: Prentice-Hall

Hyun, K.K., Mitra, S.K., Jeong, K., Tok, A., 2021. Understanding The Effects of Vehicle Platoons on Crash Type and Severity. *Accident Analysis & Prevention*, Volume 149, p. 105858.

Khassawneh, O., Mohammad, T., Ben-Abdallah, R., 2022. The Impact of Leadership on Boosting Employee Creativity: The Role of Knowledge Sharing as a Mediator. *Administrative Sciences*, Volume 12(4), p. 175

Kim, K., Pant, P., Yamashita, E., 2011. Measuring Influence of Accessibility On Accident Severity With Structural Equation Modeling. *Transportation Research Record*, Volume 2236(1), pp. 1–10

Lee, J-Y, Chung, J-H, Son, B., 2008. Analysis of Traffic Accident Size for Korean Highway Using Structural Equation Models. *Accident Analysis & Prevention,* Volume 40(6), pp. 1955–1963

Loehlin, J.C., 2004. *Latent Variable Models: An Introduction to Factor, Path, and Structural Equation Analysis.* 4th Edition. London: Lawrence Erlbaum Associates

McQuitty, S., 2004. *Statistical Power and Structural Equation Models in Business Research. Journal of Business Research*, Volume 57 (2), pp. 175–183

McQuitty, S., Wolf, M., 2013. Structural Equation Modeling: A Practical Introduction. *Journal of African Business,* Volume 14(1), pp. 58–69

Schumacker, R.E., Lomax, R.G., 2004. *A Beginner's Guide to Structural Equation Modeling*. 2nd Edition. London: Lawrence Erlbaum Associates, Inc

Sevenster, A., Farah, H., Abbink, D., Zgonnikov, A., 2023. Response Times In Drivers' Gap Acceptance Decisions During Overtaking. *Transportation Research Part F: Transportation Research Part F: Psychology and Behaviour*. Volume 94, pp. 329–340

Siregar, M.L., Tjahjono, Yusuf, N., 2022. Predicting the Segment-Based Effects of Heterogeneous Traffic and Road Geometric Features on Fatal Accidents. *International Journal of Technology,* Volume 13(1), pp. 92–102

Sumaryo, S., Halim, A., Ramli, K., Joelianto, E., 2019. A Model for Accelerating Discharge of Lane Traffic to Facilitate Intersection Access by EVs. *International Journal of Technology,* Volume 10(1), pp. 116–125

Tabachnick, B.G., Fidell, L.S., Ullman, J.B., 2007, *Using Multivariate Statistics.* 5th Edition. New York: Allyn and Bacon

Teo, T., Tsai, L.T., Yang, C.-C., 2013. Applying Structural Equation Modeling (SEM) in Educational Research: An Introduction. In: *Application of Structural Equation Modelling in Educational Research and Practice*, Khine, M.S., (ed.), Rotterdam/ Boston / Taipei: Sense Publishers

Trapsilawati, F., Li, F., Yisi, L., 2023. Ergonomics Considerations in Air Traffic Conflict Detection and Resolution. *International Journal of Technology,* Volume 14(4), pp. 898–910

Xu, C., Li, D., Li, Z., Wang, W., Liu, P., 2018. Utilizing Structural Equation Modeling And Segmentation Analysis in Real-Time Crash Risk Assessment on Freeways. *KSCE Journal of Civil Engineering*, Volume 22(7), pp. 2569–2577

Yang, D., Xie, K., Ozbay, K., Yang, H., 2021. Fusing Crash Data and Surrogate Safety Measures For Safety Assessment: Development of a Structural Equation Model With Conditional Autoregressive Spatial Effect and Random Parameters. *Accident Analysis & Prevention*, Volume 152, p. 105971

Zgonnikov, A., Abbink, D., Markkula, G., 2022. Should I Stay or Should I Go? Cognitive Modeling of Left-Turn Gap Acceptance Decisions in Human Drivers. *Human Factors*. Volume 2022, p. 00187208221144561