

## Article

# Analyzing Safety Concerns of (e-) Bikes and Cycling Behaviors at Intersections in Urban Area

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**Abstract:** Extensive effort has been devoted to examining the causal relationship between contributing factors and injury severities. Given the important role of riders' behaviors in traffic conflicts, this paper aims to analyze the causal effects of traffic conflicts resulting from riders' behaviors at intersections. The authors collected video data on 152 traffic conflicts caused by riders' dangerous behaviors in Jiangning District, China. This paper proposes a Bayesian-structural equation modeling (BSEM) approach. Based on the obtained BSEM path coefficient diagram, the factor loadings and path coefficients are analyzed to unveil the potential influence of factors, including personal features, dangerous behavior tendency, temporal and spatial characteristics of dangerous behavior, and the external environment. The results show that compared to human factors, environmental factors have a less direct impact on the severity of traffic conflicts; instead, they have an indirect positive impact on traffic conflicts by affecting behaviors. That is, if riders judge that road conditions are not suitable to conduct dangerous behaviors, they become more cautious in view of current road conditions and time revenue. Furthermore, dangerous cycling behaviors that continue to encroach on the time and space of motorized vehicles are prone to be more dangerous. The dangerous behaviors that continuously encroach on the time and space of motor vehicles (e.g., disobeying traffic signals and riding in a motorway) are significant predictors of serious conflicts. Considering the heterogeneity of riding behavior, these findings could be applied to develop effective education and intervention programs for preventing riders' high-risk behaviors and improving the traffic environment.

**Keywords:** urban transport; safety concerns of (e-) bikes; Bayesian structural equation modeling; cycling behaviors



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## 1. Introduction

Traffic safety at urban intersections is one of the most challenging issues worldwide. Vehicles coming from different directions converge at the intersections and increase traffic conflicts. In a report by the Chinese Ministry of Public Security, crashes that occurred in intersections accounted for around 30% of the total number of crashes [1]. Moreover, (e-) bikes were involved in over 25% of all intersection crashes [1]. Of these accidents involving bikes, 70.0% of riders sustained minor injuries, 12.6% serious injuries, and 10.6% died [2].

Numerous studies have been devoted to identifying and quantifying the causal relationships between contributing factors and traffic accidents. Environmental factors (i.e., traffic conditions, road characteristics, and natural environment) and human factors (i.e., riding behavior, riders' demographic, physical, and psychological characters) are proved to significantly affect the severity of accidents. Among them, riding behavior has been recognized universally as a major contributor to traffic accidents [3]. The relationships between riding behavior and other contributing factors have been widely discussed [4]. However, the studies on traffic accidents generally deal with riding behavior in parallel with other factors reported in crash reports [5]. Neglecting these correlations of riding behavior with other factors may result in unobserved heterogeneity and biased parameter

estimates [6]. Hence, it is necessary to explore the related links from contributing factors through riding behavior to traffic accidents.

Although the possible correlation is universally accepted [7,8], simultaneous incorporation of riding behavior and other contributing factors into traffic accident modeling is limited due to data availability [5]. Accident statistics collection is a time-consuming process, and the behavior data are often difficult to procure [9]. There are also some limitations that riders observed in accidents may not be a representative sample of the riding population [10]. As an alternative, traffic conflict techniques, such as post encroachment time (PET), have proven to be effective surrogate safety measures in road safety analysis [11].

This study explores a framework to qualify how contributing factors (i.e., riders' personal attributes and external environmental conditions) influence dangerous riding behavior and further influence the severity of traffic conflicts. We utilize data obtained from video surveys to capture the behavioral variables and environmental variables at the time of conflicts. We propose a Bayesian-structural equation modeling (BSEM) approach in an effort to analyze the multiple cause effects of cycling conflicts at intersections. Based on the obtained BSEM path coefficient diagram, the factor loadings and path coefficients are analyzed to unveil the potential influence of factors, including personal features, dangerous behavior tendency, temporal and spatial characteristics of dangerous behavior, and the external environment. The proposed approach is beneficial to provide a reference for improving intersection safety.

The remainder of this study is organized as follows. Section 2 reviews the literature on the causal relationships between traffic accidents and contributing factors, including behavioral factors. Section 3 describes the Bayesian structural equation modeling approach. The results are then presented and discussed in Sections 4 and 5. Finally, conclusions are provided in the last section.

## 2. Literature Review

Previous studies have investigated the quantitative relationships between cycling accident severities and factors, including environmental factors and human factors. Table 1 summarizes the contributing factors to serious cycling accidents.

Among the environmental factors, it has been proved that unsignalized intersections [12] and a higher speed limit [13] aggravate cycling injuries. Research also showed that traffic conditions such as signal control at intersections [12] and the speed limit [14] are significantly correlated to injury severity. Opinions were divided over the influence of weather and time of day. The heterogeneous effects were considered to be related to rider behavior. In addition, different sets of human factors have been discussed in studies adopting specific data collection approaches. Most studies documented that age [15] and gender [16] are related to accident severity. Research based on the crash report found that riders impaired by drugs [17] and alcohol [18] are more likely to sustain serious injuries. The use of reflective equipment [15] and helmets [19] protects riders from disastrous accidents. Self-reporting data were used to examine the relationships between accident severity and psychological factors such as riding habits [16] and risk perception [20].

Research on the role of behavioral factors in accident severity is limited due to data unavailability [5]. It is a common practice to parallel behavioral factors with other factors reported in crash reports. Dangerous riding behaviors such as distractions [12], disobeying traffic signals [17], speeding [21], etc., have been proven to have a statistical influence on safety.

In the studies focused on dangerous riding behaviors, the factors contributing to serious accidents increase the dangerous behavior rate based on self-reports or videos. For example, Zhang [22] found that the traffic density of non-motorized vehicles strongly affects riders' illegal occupancy behavior. A higher speed limit leads riders to fail to give way when turning [3]. A long waiting time at red lights [23], low density of motorized vehicles [24], and riding at the peak of morning [25] are in correlation with disobeying traffic signals. Among human factors except behavior, male riders and young riders are

more likely to commit dangerous behaviors. The improper behavior rate declines with an increase in risk perception [24]. Being used to violation [26], being alone [27], or presence of other rider violations [28] have been identified as critical precursors to committing violation behaviors.

In summary, dangerous behaviors mediate the relationship between the factors (i.e., environmental factors and riders' demographic physical and psychological characteristics) and the accident severity. As revealed in Table 1, there are compelling reasons to believe that two accidents in the same environment can be affected by heterogeneity due to the riders' behaviors and how that affects the traffic accidents.

Most studies employed regression models (e.g., the multinomial logit model [18], ordered probit model [12,29], binary logit model [3,17], random parameters logit model [21], mixed logit model [30], and logistic regression model [31]) to analyze the effect of environmental and human variables on accident severity. Regression models were also applied to identify environmental factors and demographic characteristics (e.g., logistic regression [24,27], multinomial logit model [3]). However, the simultaneous incorporation of environmental factors and human factors into traffic conflict regression modeling is limited. A critical problem of regression models is that just a single variable is evaluated at one time, given that other variables remain unchanged [32,33]. Meanwhile, the influence of behavioral factors and the important interactive effect among variables cannot be depicted.

In a study, Liu [5] performed a path analysis to deal with the mediating effects of behavioral variables in accidents. A growing number of quantitative studies have adopted the structural equation model (SEM) to investigate the influence of psychological factors on dangerous behaviors [34–37]. SEM is a method that can analyze multiple dependent and independent variables and multiple chains of effects. It integrates factor analysis and path analysis to test the direct and indirect impacts between variables in a single model. In SEM, unobservable variables can be measured, and measurement errors can be considered in the estimation process [38]. Hence, SEM is suitable for analyzing the causal relationships between human factors (i.e., personal features, behavioral intention, and behavior), environmental factors, and traffic conflicts.

**Table 1.** Summary of prior studies on cycling accident severity and dangerous behaviors.

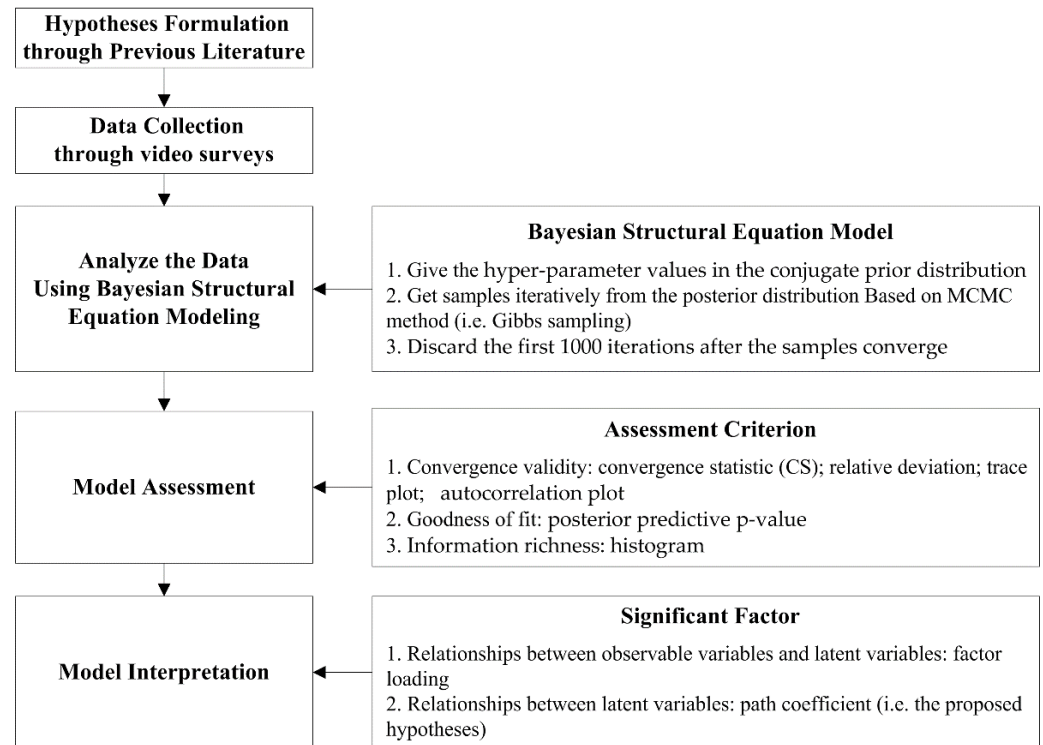
Contributing Factors		Factors Causing Severe Injury	Factors Causing Risky Behavior
Environmental factor			
Traffic condition	Signals	<ul style="list-style-type: none"> <li>Unsignalized intersections [12];</li> </ul>	<ul style="list-style-type: none"> <li>Long waiting time at red lights [23,27,28];</li> </ul>
	Speed limit	<ul style="list-style-type: none"> <li>Higher speed limit [13];</li> <li>Speed limits of 60 km/h [31]</li> </ul>	<ul style="list-style-type: none"> <li>High speed limit [3];</li> </ul>
	Traffic density	-	<ul style="list-style-type: none"> <li>Low density of motorized vehicles [22,24,39];</li> </ul>
Road characteristic	Road layout	<ul style="list-style-type: none"> <li>Roads without division [3,12];</li> <li>Narrow cycling facilities or carriageways [40];</li> </ul>	<ul style="list-style-type: none"> <li>Roads without landscaped divider [22,41];</li> </ul>
	Road condition	<ul style="list-style-type: none"> <li>Dry road surfaces [31];</li> <li>Smooth roads [12];</li> </ul>	<ul style="list-style-type: none"> <li>Abnormal road surface [3];</li> </ul>

Table 1. Cont.

Contributing Factors		Factors Causing Severe Injury	Factors Causing Risky Behavior
	Road illumination	<ul style="list-style-type: none"> <li>Night without street light [3,18];</li> </ul>	
Natural environment	Weather	<ul style="list-style-type: none"> <li>Inclement weather [18];</li> <li>No precipitation [12];</li> </ul>	<ul style="list-style-type: none"> <li>Rainy days [22];</li> <li>Sunny days [42];</li> </ul>
	Time of day	<ul style="list-style-type: none"> <li>Riding at night [31];</li> </ul>	<ul style="list-style-type: none"> <li>Riding at morning peak [22,25];</li> </ul>
Human factor		-	
Demographic character	Age	<ul style="list-style-type: none"> <li>Being Old [15,31]</li> </ul>	<ul style="list-style-type: none"> <li>Being young [3,27];</li> </ul>
	Gender	<ul style="list-style-type: none"> <li>Being male [3,16];</li> </ul>	<ul style="list-style-type: none"> <li>Being male [27,41,43];</li> </ul>
Physical character	Protective equipment	<ul style="list-style-type: none"> <li>Not wearing reflective clothing [15];</li> <li>Not wearing helmets [19,31];</li> </ul>	<ul style="list-style-type: none"> <li>Not wearing helmets [4];</li> </ul>
	Alcohol or drug	<ul style="list-style-type: none"> <li>Being intoxicated [12,17,18];</li> <li>Being impaired by drugs [17]</li> </ul>	-
	Type of vehicle	-	<ul style="list-style-type: none"> <li>Electric bicycle (compared with Bicycle) [22,28];</li> </ul>
Psychological character	Riding habits	<ul style="list-style-type: none"> <li>Frequent aggressive driving [16];</li> </ul>	<ul style="list-style-type: none"> <li>Being used to running at red-light period [26];</li> </ul>
	Risk perception	<ul style="list-style-type: none"> <li>Low risk perception [16,20]</li> </ul>	<ul style="list-style-type: none"> <li>Low risk perception [24];</li> </ul>
	Conformity tendency	-	<ul style="list-style-type: none"> <li>Being alone; [27,43];</li> <li>Presence of other rider violations [27,28]</li> </ul>
Riding behavior	Distractions	<ul style="list-style-type: none"> <li>Narrow focus [41]; Being distracted [12];</li> </ul>	-
	Traffic violation	<ul style="list-style-type: none"> <li>Disobeying traffic signals [3,17];</li> <li>Speeding-involved [18,21];</li> <li>Riding on wrong side of road [21];</li> <li>Running off the road [21];</li> </ul>	-
	Improper behavior	<ul style="list-style-type: none"> <li>Impulse behavior [16];</li> <li>Failing to give way when turning [3]</li> </ul>	-

### 3. Methodology

This paper explored the quantitative relationships between traffic conflicts, riders' dangerous behaviors, and their contributing factors using the Bayesian-structural equation modeling. The analysis of the methods was performed in five steps. Figure 1 shows the research flow, and pertinent details are provided in the subsequent subsections.



**Figure 1.** Flowchart of the data analysis.

#### 3.1. Research Design

A variety of theoretical and practical measures are developed for the cause analysis of dangerous behavior and traffic conflict. The research mentioned in Section 2 shows that riders are affected by their personal features and road and traffic conditions at intersections. These contributing factors lead to dangerous behavior tendencies. The riders' dangerous behavior causes them to deviate from their proper trajectory and becomes an obstacle in the passage of motor vehicles, thus resulting in traffic conflicts.

We proposed Hypotheses 1–5 based on the safety-related driver model [44,45] and the risk driving behavior theory proposed by Rimmö [46]. The five hypotheses which attempt to validate in this study are given below:

**Hypotheses 1 (H1).** *Properties of riders are significantly interconnected to their behavioral intentions;*

**Hypotheses 2 (H2).** *Behavioral intentions of riders are significantly interconnected to the temporal and spatial characteristics of their behaviors;*

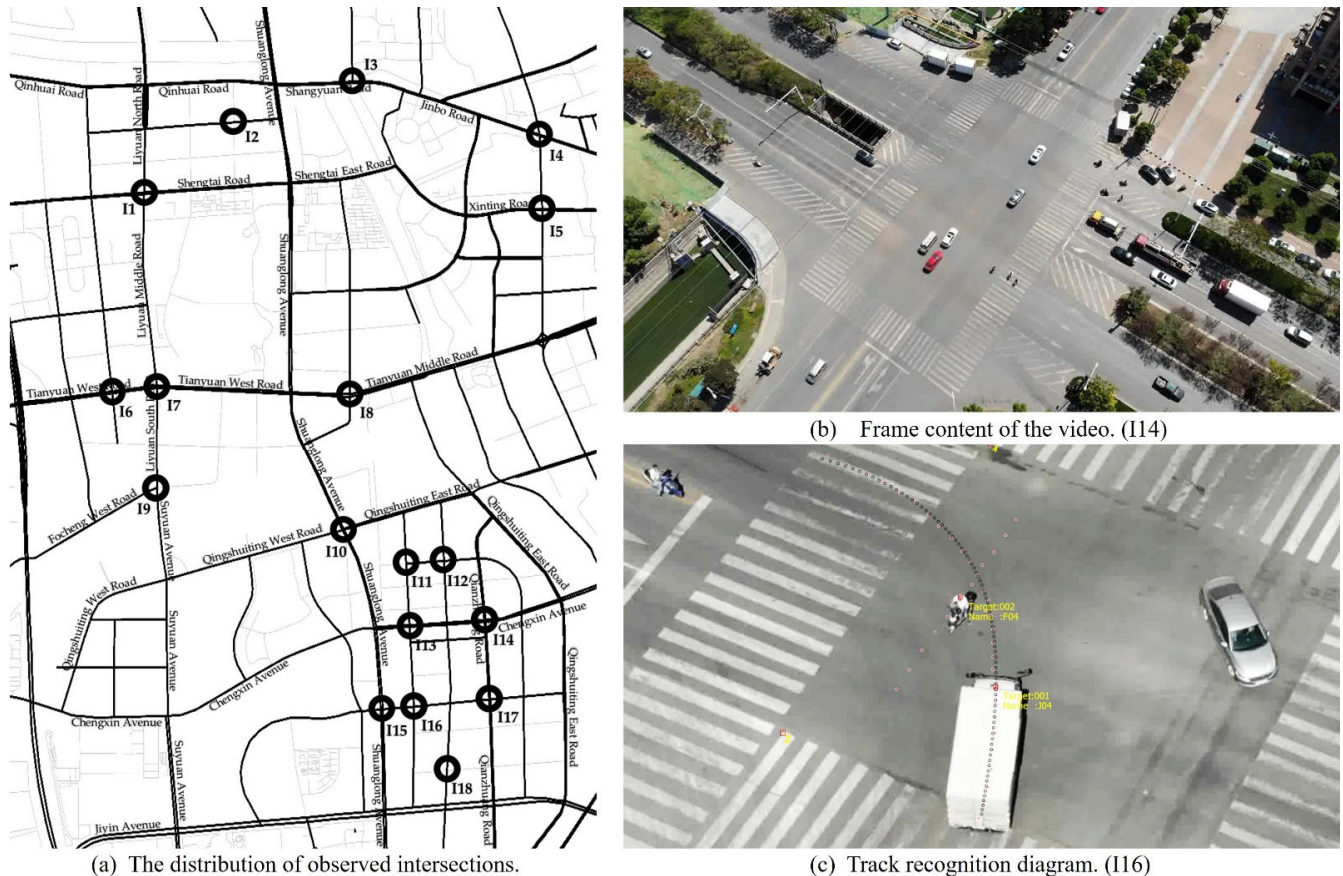
**Hypotheses 3 (H3).** *The temporal and spatial characteristics of riders' behaviors are significantly interconnected for the traffic conflict indicator (i.e., PET);*

**Hypotheses 4 (H4).** *Road and traffic conditions are significantly interconnected for riders' behavior intentions;*

**Hypotheses 5 (H5).** *Road and traffic conditions are significantly interconnected for the traffic conflict indicator (i.e., PET).*

### 3.2. Data Collection

To capture the dangerous behavior of riders and associated traffic conflicts, we conducted video surveys in September and October of 2019. We selected a total of 18 signalized intersections with different numbers of lanes and signal timing in Jiangning District, Nanjing, China, as observation points (see Figure 2a). We used a drone to record the observation points at an angle close to vertical during the peak hours from 17:00 to 18:00 (see Figure 2b).



**Figure 2.** Study area and conflict identification.

We manually calculated the property data (i.e., age, gender, vehicle, and vehicle loadings), behavior data of riders, and road condition data using video observation. In the rider property data, whether the rider is young, middle-aged, or old was judged by the characteristics of appearance and the flexibility of movements.

We used the Image Processing Technique to obtain corresponding traffic conflict data. Post encroachment time (PET) was commonly used as a surrogate safety measure to assess traffic conflict. Traffic conflicts between motorized vehicles and bikes caused by the dangerous behaviors of riders were identified in George2.1 software. The software developed by Nagoya University can capture the trajectories of the conflicting parties separately (see Figure 2c). We referred to the Surrogate Safety Assessment Model proposed by the Federal Highway Administration (FHWA) [47]. The model sets the value range of PET from 0 to 5 s. Therefore, we excluded PET data above 5 s. In addition, we classified the severity of traffic conflicts into three categories, referring to the studies of Long [48] and Ma [49]. We chose 15% and 85% quantile values of the cumulative frequency distribution to divide the severity of conflicts into three categories.

We collected data on 18 observable variables based on field surveys and video recordings. A total of 152 representative samples of traffic conflicts caused by dangerous behavior at 18 intersections were obtained.

### 3.3. Establish the Bayesian-Structural Equation Model

#### 3.3.1. Structural Equation Model

SEM includes the measurement model and the structural model, containing latent variables, observable variables, and interference or error variables. The measurement model reflects the covariation effect of latent variables with a set of observed variables. The structural model then reflects the causal relationships between latent variables.

The measurement model can be expressed as:

$$y = \Lambda_y \eta + \varepsilon \quad (1)$$

$$x = \Lambda_x \xi + \delta \quad (2)$$

The structural model can be expressed as:

$$\eta = B\eta + \Gamma\xi + \zeta \quad (3)$$

where  $y$  and  $x$  are the observed variables that are the respective indicators of  $\eta$  and  $\xi$ ,  $\eta$  represents an endogenous latent variable (dependent variable) vector,  $\xi$  represents an exogenous latent variable (independent variable),  $\Lambda_y$  and  $\Lambda_x$  are the factor loading matrixes,  $B$  describes the relationships among latent variables in  $\eta$ ,  $\Gamma$  describe the influence of  $\xi$  on  $\eta$ , and  $\varepsilon$ ,  $\delta$ , and  $\zeta$  are the measurement error terms.

#### 3.3.2. Model Fitting

The Maximum Likelihood (ML) method is the most popular method for estimating SEM. However, when estimating models with complex constructs, the ML method may experience identification problems and obtain invalid statistics. The ML method is analyzed based on the covariance matrix of the observations, so the stability of the parameter estimation results and the fitness test are closely related to the sample size. Consequently, this method is applicable to address a large sample size. In contrast, the Bayesian method on the basis of sampling relies less on the asymptotic theory, which reduces the requirements for sample size and data distribution. To test the mediating effects, the assumption of multivariate normality should be satisfied by the ML method, which is possibly insufficient in practical application. However, this is not necessary for the Bayesian method. Additionally, the results obtained by the Bayesian estimation with fuzzy prior information can provide higher accuracy and testability [50]. Therefore, considering the multidimensional constructs containing mediating effects and specific selection criteria for samples, we apply the Bayesian method to estimate SEM (BSEM) research hypotheses were tested using the BSEM approach to avoid the identification problem that may exist in complex models and obtain more effective statistics simultaneously.

The improvement of the Bayesian method to the traditional SEM mainly lay in the adjustment of parameter estimation. Given the observed dataset of raw observations  $Y$  and the prior probability distribution function (PDF)  $p(\theta)$  of the uncertain system parameters  $\theta$ , the posterior PDF  $p(\theta|Y)$  is given by

$$p(\theta|Y) = \frac{p(Y|\theta)p(\theta)}{\int p(Y|\theta)p(\theta)d\theta} \quad (4)$$

The prior information related to the parameters is integrated by determining the conjugate prior distribution. The hyper-parameter values in the conjugate  $p(\theta)$  are given according to the theory or previous research results. Parameters such as the mean, variance, etc., of the posterior distribution  $p(\theta|Y)$  are useful for statistical inference. These quantities can be obtained using sufficient observations drawn from  $p(\theta|Y)$ . However,  $p(\theta|Y)$  is not in closed form and is too complicated to derive directly for most SEMs. Previous studies [51,52] applied the Markov Chain Monte Carlo (MCMC) methods (e.g., Gibbs sampling) to draw observations iteratively from arbitrary multivariate PDFs to simulate observations. Suppose that the vector  $\theta$  is decomposed into  $N$  components:

$\theta = (\theta_1, \theta_2, \dots, \theta_i, \dots, \theta_N)$ . In the Gibbs sampling algorithm, at the  $i$ -th iteration with values  $\theta_{1:i-1}^* = [\theta_1^{*T} \theta_2^{*T} \dots \theta_{i-1}^{*T}]^T$  and  $\theta_{i+1:N} = [\theta_{i+1}^T \theta_{i+2}^T \dots \theta_N^T]^T$ , the full conditional PDFs  $p(\theta_i^* | \theta_{1:i-1}^*, \theta_{i+1:N}, Y)$  are required to perform an alternating conditional sampling. In this way, sufficient samples are collected by Gibbs sampling. Lastly, discard the first 1000 iterations, and the desired posterior distribution is obtained after the samples converge.

The authors analyzed data using the Bayesian estimation procedure in AMOS 24.0.

### 3.3.3. Model Assessment

The parameter estimation results of BSEM will dynamically change during and after convergence. The result obtained is a posterior distribution rather than a fixed value. Bayesian estimation may not converge as the number of iterations increases. In order to confirm that the Markov chain has finished with proper posterior distribution, it is necessary to assess the convergence validity.

Three convergence criteria should be satisfied. Firstly, the convergence statistic (CS) of the whole model and each parameter should be less than 1.0020. When the CS value approaches 1.0, generating additional samples makes little difference [53]. Secondly, to avoid local convergence, the relative deviation of results obtained after the different number of iterations should be computed. The level of relative deviation should be below the changeable threshold, which is related to the specific coefficient [54]. Lastly, the trace plot and autocorrelation plot of each parameter should be visually checked. Trace plots illustrate the model parameters and spatial random effects of the posterior samples. If the chain of each parameter shows no obvious fluctuations or random, it can be considered convergence [54]. An autocorrelation plot is a plot of iterations vs. sampled values for each variable in the chain, with a separate plot per variable. The correlation values in the autocorrelation graph of each parameter should gradually approach 0 [53].

In addition, Bayesian estimation provides the posterior predictive  $p$ -value to measure the general goodness of fit. The  $p$ -value is close to 0.5, indicating that the model fits well. If the  $p$ -value is close to 0 or 1, indicating that the estimated value is very different from the actual observed value, and the fitting is not good [55]. The histogram should also be visually checked to determine the information richness. It represents the posterior information of each parameter most intuitively and completely [54]. The histogram of each parameter should be smooth without gaps; otherwise, the estimation result may have no substantial significance [56].

### 3.3.4. Model Interpretation

We used factor analysis to analyze the measurement model. The factor loading determines whether the observed variables could represent latent variables well. When the factor loading is  $\pm 0.3$ ,  $\pm 0.4$ , and  $\pm 0.5$ , the correlation level is classified as “minimal level,” “important,” and “practically significant,” respectively [57].

Generally, the path analysis of the results of the structural model receives more attention. The standardized path coefficient estimates,  $p$ -values, etc., should be reported to analyze the causal relationships between latent variables [58]. For the hypothesized relationships, the posterior credible intervals of path coefficients (at 0.05 level) should be checked. If the value zero lies within the credible interval (CI), the hypothesis will not be supported. Then, it is necessary to determine whether the symbol of the path coefficient conforms to the definition of the hypothesis. If so, the hypotheses will be supported, or they will be rejected [54]. Furthermore, BSEM introduced mediating variables. The indirect effects should be reported, which are defined as the product of path coefficients of the independent variable on dependent variables through all mediate variables [59].

## 3.4. Model Development

The BSEM in this study contains a total of 4 latent variables. The properties of riders and the road and traffic conditions were defined as exogenous latent variables. It means the two variables were not affected by any other variable. Behavior intentions of riders



and temporal and spatial characteristics of riders' behaviors were defined as endogenous latent variables and affected by other latent variables and error terms. In addition, the PET was defined as an observable variable. Latent variables were measured by corresponding observable variables, and the variables involved were shown in Table 2.

**Table 2.** SEM variable system.

Variable	Meaning (Unit)
Properties	
Is male	1 = male; 0 = female
Is middle aged	1 = middle aged; 0 = not middle aged
Is old	1 = old; 0 = not old
Is rider	1 = rider; 0 = E-rider
Is carrying things	1 = carrying things; 0 = not carrying things
Is carrying people	1 = carrying people; 0 = not carrying people
Behavioral intentions	
Visual search	The number of head turns of the rider upon reaching an intersection (times)
Action change	The number of times a rider changes his position or posture by moving or swinging
Contact with other riders	The number of contact between the rider and other riders, such as spoken words, eye contact, gestures, etc. (times)
Waiting time	The time difference between the moment the rider begins to take dangerous behavior and the next passable moment (seconds)
Behavior characteristics	
Length of encroachment time	Duration of the entire cycle of dangerous behavior (seconds)
Amount of encroachment space	The product of the width of the bike (1 m) and the length of the trajectory when the rider behaves dangerously (m <sup>2</sup> )
Traffic flow in the space	The total number of motor vehicles in conflicting directions of the rider's when the rider behaves dangerously (PCU)
Road and traffic conditions	
Green signal ratio	The green signal ratio of the intersection where the rider is located
Number of lanes crossed	The total number of lanes in each direction that a rider needs to cross when crossing an intersection
Intersection area	The area of the intersection where the rider is located (m <sup>2</sup> )
Amount of bikes in the same direction	The total number of bikes in the same direction as the rider's in a minute (PCU/min)
Motorized vehicle flow in the conflict direction	The flow of motor vehicles in all directions that conflict with the riding direction of the rider (PCU/min)
Endogenous measured variable	
PET	0 = potential collision (3.6 s < PET ≤ 5 s); 1 = ordinary potential collision (2.5 s < PET ≤ 3.6 s); 2 = serious potential collision (PET ≤ 2.5 s)
Other measured variable	
Angle of conflict ( $\theta$ )	0 = $\theta \in [0,45]$ ; 1 = $\theta \in (45,135]$ ; 2 = $\theta \in (135,180]$

The observable variables including gender, age, transportation, and loading were all set as dummy variables. The raw data of road and traffic conditions with a positively skewed distribution were compressed with a logarithmic transformation. The sample

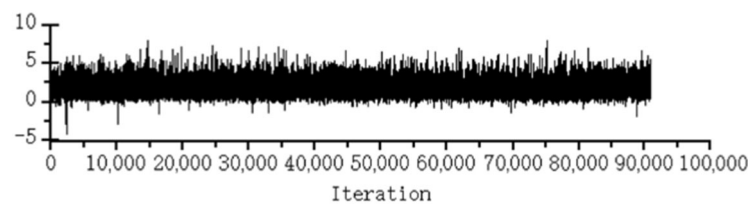
data coming from all variables except dummy variables were normalized to zero mean to accelerate the convergence of the model.

Bayesian estimation was performed on the constructed SEM. We used uniform non-informative priors, which were set to default. Given the observed data, the model estimated the posterior probability distribution using the MCMC sampling method. The first 1000 iterations were discarded.

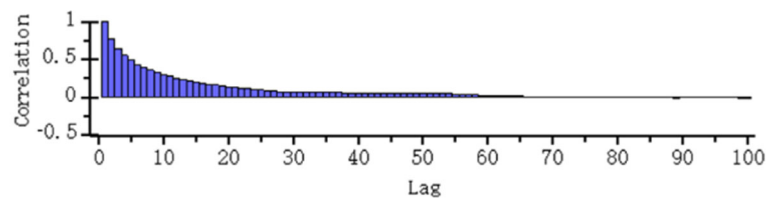
## 4. Results

### 4.1. Model Assessment

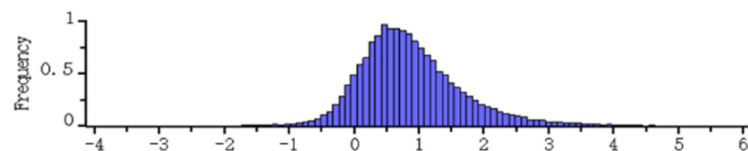
The three convergence criteria mentioned in Section 3.3.3 were satisfied. After 50,213 iterations and 91,018 iterations, the overall convergence indexes C.S. were 1.0007 and 1.0005, respectively, which were both lower than 1.0020, indicating that the model had converged as a whole. For the two chains with different iterations, the relative deviation of the results obtained under 50,213 iterations and 91,018 iterations was less than 2%, indicating the chains stabilized in the same area of the parameter space. As a result, full chain convergence was obtained, and the results obtained under 91,018 iterations could be used for further analysis. For the single-chain extending to 91,018 iterations, the convergence index of each parameter was less than 1.0002, which was close to the expected value of 1.0000. The trace plot of each parameter showed no obvious fluctuations or random drift (see Figure 3a). The correlation values in the autocorrelation graph of each parameter all approached 0 gradually (see Figure 3b). These results showed that all parameters converged well.



(a) Trace plot of  $\gamma_1$ .



(b) Autocorrelation graph of  $\gamma_1$ .



(c) Histogram of  $\gamma_1$ .

**Figure 3.** Visual validity test using  $\gamma_1$  as an example.

Overall, the BSEM approach for effects of non-motorized vehicle riders' dangerous behaviors on traffic conflicts has good adaptability, effectiveness, and convergence stability.

The posterior prediction  $p$ -value used as an indicator of the overall goodness of fit was 0.50, which was consistent with the expected value of 0.50, indicating that the hypothetical model fits well with the observed data.

In the validity test of model parameters, the normalized posterior distribution means of each parameter satisfied the requirement of statistical significance within a 95% credible

interval. The histogram of each parameter was smooth without gaps, indicating that the posterior distributions make substantive sense (see Figure 3c).

4.2. Results Analysis

Figure 4 shows the direct effect path diagram of the model obtained according to the estimation results of BSEM. Factor analysis and path analysis are performed on the measurement model and the structural model, respectively. The corresponding factor loadings and path coefficients reveal the positive or negative influence between variables, the magnitude of which indicates the degree of influence.

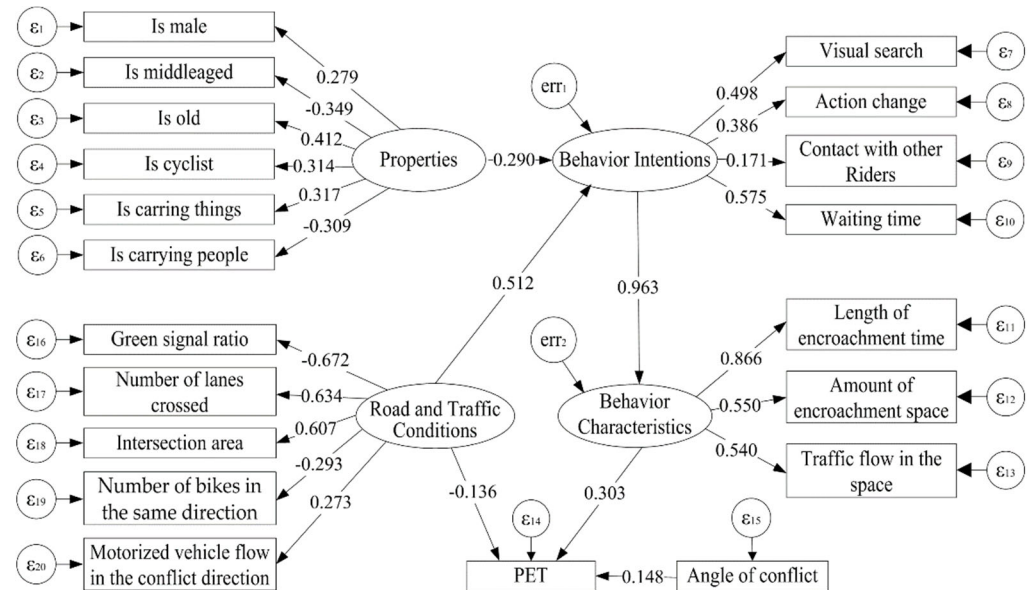


Figure 4. BSEM standardized direct effect path diagram.

Table 3 presents the indirect effects derived from properties of riders, behavior intentions, and road and traffic conditions for the two endogenous variables, behavior characteristics, and PET.

Table 3. Results of standardized indirect effect estimation.

	Properties	Road and Traffic Conditions	Behavior Intentions
Behavior Characteristics	0.279 ***	0.493 **	0.000
PET	0.085 **	0.149 **	0.292 **

Notes: \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

4.2.1. Factor Analysis

- On the measurement model of properties of riders, age shows the most significant effect on properties, followed by loading situation. Being middle-aged (factor loading = 0.349,  $p < 0.05$ ) and being old (factor loading = 0.412,  $p < 0.05$ ) have relatively significant effects on personal properties. Therefore, other conditions being equal, the elderly are most prone to dangerous riding behavior, followed by young riders and middle-aged riders. Carrying things (factor loading = 0.317,  $p < 0.05$ ) is positively correlated to personal properties, while carrying people (factor loading = -0.309,  $p < 0.05$ ) is negatively correlated. This means that riders carrying things are more likely to induce dangerous behaviors, and carrying people has a certain inhibitory effect on riders' dangerous behaviors. Male riders and E-riders are more likely to induce dangerous behaviors than female riders and bicycle riders.

- (2) Among the measured variables corresponding to the traffic road environment, the green signal ratio (factor loading =  $-0.672$ ,  $p < 0.001$ ) and the number of bikes (factor loading =  $-0.293$ ,  $p < 0.05$ ) in the same direction show a negative impact. It is found that when the intersection has a high green signal ratio and a large number of riders in the same direction, it is friendlier to riders, and the green signal ratio has a greater impact. The mean values for the number of lanes crossed (factor loading =  $0.634$ ,  $p < 0.01$ ), intersection area (factor loading =  $0.607$ ,  $p < 0.01$ ), and motorized vehicle flow (factor loading =  $0.273$ ,  $p < 0.01$ ) in the conflict direction are all positive. When the number of other riders in the direction is large, the intersection has a certain deterrent effect on riders who violate the regulations.
- (3) Among the four measured variables corresponding to the dangerous behavior tendency, waiting time (factor loading =  $0.575$ ,  $p < 0.01$ ), visual search (factor loading =  $0.498$ ,  $p < 0.05$ ), and action change (factor loading =  $0.386$ ,  $p < 0.05$ ) are observed to represent the anxious psychology. They all show significant positive relationships with the increase in dangerous behavior tendency. It indicates that riders are prone to dangerous behaviors under the comprehensive consideration of the waiting time and the tolerable time. In contrast, the contact with other has riders has relatively little effect on the behavior tendency (factor loading =  $0.171$ ,  $p < 0.05$ ).
- (4) Concerning the temporal and spatial characteristics of riders' behaviors, we observe that all measured variables present significant factor loadings, equal to or higher than  $0.50$  at the  $0.05$  level. Among them, the length of encroachment time (factor loading =  $0.866$ ,  $p < 0.01$ ) is most correlated to the state of the rider's encroachment on the time and space of the motorized vehicle. It is able to represent the speed and pause of the rider during encroachment. So the observation of the length of encroachment in the time dimension has a greater impact on the characterization of dangerous behaviors.

#### 4.2.2. Path Analysis

The properties of riders (path coefficient =  $0.290$ ,  $p < 0.05$ , 95% CI =  $[0.069, 0.589]$ ) and the road and traffic conditions (path coefficient =  $0.512$ ,  $p < 0.01$ , 95% CI =  $[0.332, 0.712]$ ) have a significant direct impact on the riders' dangerous behavior tendency. The riders' dangerous behavior tendency significantly and directly affects the temporal and spatial characteristics of riders' dangerous behavior (path coefficient =  $0.963$ ,  $p < 0.01$ , 95% CI =  $[0.723, 0.993]$ ). The road and traffic conditions (path coefficient =  $-0.136$ ,  $p < 0.05$ , 95% CI =  $[0.037, 0.353]$ ) and the characteristics of dangerous behavior (path coefficient =  $0.303$ ,  $p < 0.01$ , 95% CI =  $[0.063, 0.503]$ ) show a significant direct impact on PET. The road and traffic conditions are indirectly related to the PET with the value of  $0.149$  ( $p < 0.05$ , 95% CI =  $[0.014, 0.407]$ ), which offset the direct effect and yield little effect in total.

Combined with factor analysis, it can be obtained that when a rider has the attributes such as being male, being young or old, riding an e-bicycle, or carrying things, the endurance time at the intersection is shorter, and it is more likely to behave dangerously. The greater the tendency of the rider to behave dangerously, the more serious the encroachment of time and space would be. In the case of encroaching on a longer time, a larger space, and more motor vehicles in the space, the rider is more likely to encounter unexpected situations, thereby increasing the possibility of serious traffic conflicts with the motor vehicle. The road and traffic conditions that are not conducive for riders to behave dangerously may reduce the severity of traffic conflicts. Nevertheless, these conditions would lead to an increase in the tendency of dangerous behaviors.

## 5. Discussions

### 5.1. Results of BSEM

Human factors significantly affect the dangerous behavior of riders in traffic conflicts. Firstly, personal properties, such as gender, age, vehicle, etc., of riders significantly affect their dangerous behaviors, which is consistent with the findings of Sun [60] and Ravishankar [61]. Secondly, in terms of psychological factors, unlike most studies that used

self-reporting data to study the impact of riders' risk perception and attitude on dangerous behavior [62,63], this study is based on the data of individual micro-behavior characteristics of riders. The observable variables in the video, such as visual search, waiting time, and contact with other riders, are utilized as behavior tendencies. Similarly, the attitude was measured by two items related to waiting time (i.e., "It is important for me to save time" and "Running a red light allows me to arrive at my destination faster") in the research by Shen [64]. Ma [65] used contacts between cyclists to represent the tendency of conformity in a study on the propagation of violations. Behavioral tendencies are described in real-time and on the spot. In this way, the behavior intentions are captured at the moment and place where the user develops a tendency to behave dangerously. Therefore, individual micro behavior characteristics can depict the rider's psychological state to a certain extent. Moreover, it is found that the main driving force of riders' dangerous behaviors was attitude, while the effect of conformity psychology is relatively small, which is supported by the results of Tang [66] and Yang [67].

Compared with human factors, the direct effect of road and traffic conditions on the severity of traffic conflicts is relatively smaller (the path coefficient is  $-0.136$ ). One reason might be that in the entire system, including people, vehicles, and the environment, the influence of human-related factors is more prominent. Additionally, different riders are affected by the environment differently, so few variables are directly related to the severity of the conflict [68].

Road and traffic conditions have a negative direct impact on the severity of traffic conflicts, while their indirect impacts on traffic conflicts through dangerous behavior tendencies and characteristics are positive, which is contrary to the findings of Schleinitz [69] and Zhang [22]. As far as research methods are concerned, existing studies tend to research based on the self-reports of riders. When the interviewees are out of the actual traffic environment, they may be affected by recall bias and social expectations. The behaviors observed in real situations are more in line with the reactions and decisions of the riders at the time [70]. From a psychological point then, the sample size is small since this study focused on riders who have traffic conflicts due to their dangerous behaviors. Men account for a relatively large proportion (77%), and there are also some skilled food delivery men, who may be more adventurous and irritable [71]. In terms of model settings, among the observation variables of dangerous behavior tendencies, a visual search can also be used as a sign of vigilance to a certain extent [23]. In a traffic environment that is not friendly to riders, riders increase their visual search to avoid risks before making dangerous behaviors, increasing the dangerous behavior tendency and reducing the severity of traffic conflicts.

In general, if riders judge that the road and traffic conditions at the intersection are not conducive to behaving dangerously, they may be more vigilant in view of the current road conditions and time revenue. Under such circumstances, riders waiting in the wings can better avoid serious traffic conflicts.

This study also imposes a unified form on the description of dangerous behaviors such as running a red light, driving in reverse, occupying a motor vehicle lane in two space-time dimensions. The results show that the length of the encroachment time has a greater impact on the severity of traffic conflicts compared to the amount of encroachment space and the traffic flow in the space. Therefore, dangerous behaviors that continue to encroach on the time and space of motor vehicles are more dangerous and thus increase the possibility and severity of traffic conflicts.

### *5.2. Implications for Intervention Strategies*

Safety interventions should focus on the rider's personal properties. It is quite necessary to take educational programs for the targeted riders such as old riders and delivery riders who have to frequently carry boxes and are always in a hurry. The traffic management department of Xi'an city has provided specific education for delivery riders to reduce their violation intention [64].

Attitude significantly affects behavior intention. The basic beliefs underlying attitude are mainly from the desire to save time. Reducing unnecessary waiting time by optimizing the traffic signal control at intersections may reduce the violation intention. Riders may be more cautious in weighing the income of dangerous behaviors. In terms of environmental factors, riders are prone to committing dangerous behaviors at intersections with fewer lanes, less area, and uneven traffic density in all directions. It indicated that prominent warning signs need to be placed at these intersections. The traffic police need to be increased when the traffic in one direction is heavy.

The dangerous behaviors that continuously encroach on the time and space of motor vehicles such as disobeying traffic signals and riding on a motorway have a higher risk. The trajectory of cyclists can be constrained by road isolation facilities. Traffic signal control plans such as green waves can also discourage riders from disobeying traffic signals and prevent potentially serious conflicts [43].

## 6. Conclusions

This study investigated (e-) bikes conflicts at intersections by using data obtained from video-graphic surveys. Post encroachment time (PET) was utilized as the traffic conflict indicator to act as an effective surrogate safety measure in the road safety analysis. Considering that traffic conflict is a complex phenomenon, this paper proposed a Bayesian-structural equation modeling (BSEM) approach to explore the interrelationships (direct and indirect effects) between properties of riders, behavior intention, behavior characteristics, road and traffic conditions, and PET.

Through the estimation results of BSEM, it was found that the personal properties of riders significantly affect their dangerous behavior tendency, which further affects the time and space characteristics of the behavior and ultimately has a significant impact on the severity of the traffic conflict. When a rider has attributes such as being male, being young or old, riding an e-bicycle, or carrying things, he/she is more likely to commit dangerous behaviors. In terms of dangerous behaviors, riders are more concerned about the benefits of the violation, such as saving time. The dangerous behaviors that continuously encroach on the time and space of motor vehicles (e.g., disobeying traffic signals and riding in a motorway) are significant predictors of serious conflicts. The road and traffic conditions show a direct negative effect on traffic conflicts and exert a mediating positive effect on traffic conflicts by influencing riders' dangerous behavior tendencies and characteristics. The overall effect of road and traffic conditions on traffic conflicts is not significant.

These findings enhance our understanding of relationships between contributing factors, dangerous behaviors, and traffic conflicts. It may be beneficial to traffic managers to develop strategies to discourage dangerous behaviors and reduce serious conflicts. However, more research is needed to collect the samples from different regions and countries under other conditions such as different times of day and weather to enhance the generalizability of our findings. A questionnaire survey can be conducted to deal with the uncertainty about riding behaviors and psychological factors in future work.

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