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Investigating the Factors Affecting Rider's Decision on Overtaking Behavior: A Naturalistic Riding Research in China

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Abstract: Overtaking behavior between non-motorized vehicles is one of the main characteristics of the cycling path, and unsafe overtaking behavior has a certain negative impact on riders' safety. However, little is known about the factors affecting riders' overtaking decisions. This study aimed to identify the influence of road facilities, types of non-motorized vehicles, and human factors on the characteristics of overtaking behavior on bicycle lanes. DJI drone-based naturalistic riding research was explored in China and a random parameter logit regression model was estimated to model the overtaking decisions of non-motorized vehicle riders. The results showed that gender, age, professional deliverer, type of lead non-motor vehicle, type of non-motorized vehicles, and width of cycling lane influence overtaking behavior significantly. The present study provides theoretical evidence to strengthen the safety design and evaluation of cycling lane infrastructure.

Keywords: traffic safety; overtaking behavior; random parameter logit regression model; factor

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1. Introduction

With the acceleration of urbanization and motorization, cities have become increasingly congested. In the face of highly congested traffic, non-motorized vehicles such as electric bicycles and traditional bicycles may provide a safe alternative to overcrowded public transportation and private cars by virtue of their convenience [1,2]. Concerning sustainability, policies encouraging stronger use of the bicycle for urban compulsory trips have been introduced [3]. According to the residents' travel traffic report of a city in China in 2021, the proportion of slow-moving modes (walking, electric bicycles, bicycles) in the whole city is 47.5%, among which the proportion of electric bicycles increased from 6.5% in 2015 to 18.95% in 2021 [4]. Nevertheless, the more frequent use of electric bicycles and bicycles is also detrimental to road safety. They are not protected by metal structures like motor vehicles, resulting in more severe injuries to non-motorized vehicle riders in the event of a traffic accident [5,6]. Data released by the World Health Organization in 2018 found that half of all deaths on roads globally are among the most unprotected, with non-motorized vehicle riders being an important representation of unprotected road users [7]. In China, statistics provided by the Shenzhen Traffic Police illustrated that approximately 130,000 cases of bicycle-related violations have occurred since 2017 and the number of rider-related crashes in the first half of 2017 was 79.63% higher than the number during the same period in the previous year [7–9].

1.1. Overtaking Bicycle Riders

Overtaking behavior is a common phenomenon in traffic flow, and existing studies have analyzed the overtaking behavior of motor vehicles [10–12]. Naturalistic riding research shows that 65.7% of unsafe incidents are caused by a motor vehicle attempting to overtake riders [13]. Numerous studies have been developed to analyze the characterization of motorized vehicles to overtake cyclists using various methods, such as instrumented bicycles [14,15], naturalistic driving study [16], and driving simulators [17,18]. This has been done in a wide range of districts, ranging from rural roads to urban settings [19,20]. In addition to exploring the characterization of the interaction between a motor vehicle and a bicycle during an overloading maneuver, some scholars also assessed the overtaking of a rider's group [13,21]. In the above research, motor vehicles are mainly used as the main body of overtaking, and bicycles are the overtaken vehicles.

In order to reduce the conflict between motor vehicles and non-motorized vehicles, most cities in China will set up a physical separation between motor vehicles and non-motorized vehicles on road segments with large traffic volumes. According to China's traffic management policy, both electric bicycles and traditional bicycles are regarded as non-motorized vehicles and share bicycle lane space. In the mixed flow of bicycle lanes, there are large differences between various types of vehicles, with electric bicycles being faster and more flexible than traditional bicycles. Research shows that electric bicycles have a higher risk of sudden braking and deceleration than traditional bicycles [22].

Unlike motor vehicles, non-motorized vehicles are less obvious in car-following, and overtaking is one of the main characteristics of mixed non-motorized vehicle traffic flow. In practical engineering applications, scholars often evaluate the safety level of non-motorized vehicle lanes by the number of overtaking accidents [23,24]. Every overtaking accident can be regarded as a conflict between non-motorized vehicles, and this kind of conflict often interferes with the normal driving of the overtaken vehicles and other vehicles nearby. In turn, it has a certain negative impact on the safe operation of traffic flow in non-motorized vehicle lanes. Given the extensive use of bicycles and electric bicycles in China, the collision risk caused by overtaking accidents is common in non-motorized vehicle lanes. It is also mentioned in the Highway Capacity Manual that the safety of non-motorized vehicle lanes can be evaluated according to the overtaking accidents of bicycles, which is an important index of bicycle traffic safety risk analysis [24]. It is, therefore, of great significance to investigate the microscopic behavior characteristics of mixed bicycle traffic flow on non-motorized vehicle lanes and explore the influencing factors of overtaking behavior to strengthen the safety design and evaluation of bicycle lane infrastructure.

Up to now, only a few scholars have carried out research on overtaking accidents between non-motorized vehicles. Mohammed et al. characterized cyclist maneuvers in following and overtaking interactions [25]. Khan and Raksuntorn (2001) studied bicycle overtaking maneuvers by comparing the speeds of overtaking bicycles at different passing states [26]. Zhao et al. (2013) developed a cellular automata model for modeling overtaking decisions on bicycles [27]. Yan et al. (2018) developed width recommendations for separated bicycle lanes considering abreast riding and overtaking behaviors [28]. However, these studies were prone to develop bicycle traffic microsimulation models, and it is not clear which factors affect the overtaking behavior among non-motor vehicles, and how. Moreover, most of the existing related research obtains basic data from the perspective of naturalistic riding and driving simulation, but rarely collects data via video shooting. Drones can shoot from a top-down perspective, with relatively traditional frame size and wider fixed-camera coverage by virtue of their small size, flexibility, and convenience. In this way, more comprehensive interaction information of non-motorized vehicle flows can be obtained.

1.2. Objectives

In this paper, the influence of road facilities, types of non-motorized vehicles, and human factors are comprehensively considered to explore the characteristics of the overtaking behavior of non-motorized vehicles on bicycle lanes and its influencing factors, providing a theoretical basis for future traffic safety education and intervention scheme design. Firstly, a field survey of 12 special bicycle lanes is carried out using drone aerial photography in Hefei. Then, basic data such as traffic environment characteristics, non-motorized vehicle characteristics, and rider characteristics are extracted according to aerial close-range video.

On this basis, a random parameter logit model is constructed to analyze the influencing factors of overtaking behavior decisions. This method can make up for the fact that the traditional logistics model does not consider data heterogeneity.

In the remainder of this paper, the data extraction and study methods are described in Section 2. In Sections 3 and 4, the analysis results and discussion are presented. Finally, the conclusions of the study and its limitations are provided in Section 5.

2. Methods

2.1. Instruments

The methodology scheme is shown in Figure 1. The observational investigation was performed using two cameras for field data collection. On the one hand, data related to the static geometric parameter data of the study segments and the dynamic traffic performance of non-motorized vehicles were obtained. On the other hand, naturalistic videos from a static camera were recorded to obtain the characteristics of each rider.

Diversified methods can be used for traffic flow data surveys. Krajewski et al. compared the drone-based approach with existing measurement methods (drone, infrastructure sensors, vehicle with series-production sensors, vehicle with highly automated driving sensors) in terms of the five requirements (naturalistic behavior, static scenario description, dynamic scenario description, effort effectiveness, and flexibility) [29]. The comparison showed that drones have several strengths in terms of naturalistic behavior and static and dynamic scenario description. Unmanned aerial vehicles and cameras have recently been used in traffic safety studies including driving behaviors and riding behaviors [30].

Given the research objective of this paper, it is necessary to obtain the overtaking phenomena of non-motorized vehicles on bicycle lanes. In this survey, the DJI Drone Inspire 2 is used with an external 360° pan/tilt camera and built-in SSD storage space, which supports 4K ultra-clear video recording (30 frames per second). With its flexible maneuverability, strong hover shooting stability, support for precise hovering without GPS, and satisfactory image anti-shake effect, the aircraft can still shoot stable videos even when flying in large movements. See Figure 2 for the drone equipment and aerial photography site. In this study, it is also necessary to identify the individual attributes of riders, which cannot be clearly identified by shooting at high altitudes. Therefore, a video camera with a tripod set up on the roadside is used to capture the individual information of riders, as shown in Figure 3.

2.2. Data Acquisition Procedures

In this paper, the overtaking behavior of non-motorized vehicles in Hefei is taken as the research object. Hefei is the capital of Anhui Province and is a typical large city located in eastern China. The city's orientation, traffic characteristics, geometric road design, and riding behavior are similar to those in other major Chinese cities. By 2021, the number of electric bicycles in Hefei alone had reached 3 million [31]. Like other cities in China, Hefei has high levels of non-motorized traffic and frequent overtaking during peak hours.

Before the official start of the traffic investigation, the shooting time and place of the drone should be determined. To reduce the adverse effect of strong sunlight on the later-stage speed extraction, video capture is carried out in the evening peak hours (17:30–18:30) with fine weather. In the selection of the survey site, the following principles are followed: the bicycle has a large flow and is a relatively continuous form of exercise; there is no influence of a large canopy, telephone pole, street lamp, or other obstructions above the non-motorized vehicle lane; the flight area meets the basic requirements of drone take-off, avoiding restricted areas such as military areas; and the drones and investigators cannot adversely affect the bicycle traffic flow. To reduce the interference of motor vehicles and pedestrians on the bicycle flow, the survey segments selected in this study are all in the form of machine non-isolation. In the early stage of the pre-investigation, it was found that the road segments with isolated markings tend to have a small bicycle flow. Even if bicycles pass through, riders do not drive in the markings, and they have a high probability of occupying motor vehicle lanes. Therefore, the road segment that is physically isolated between motor vehicles and non-motorized vehicles is finally selected as the drone video acquisition point. See Table 1 for specific information.

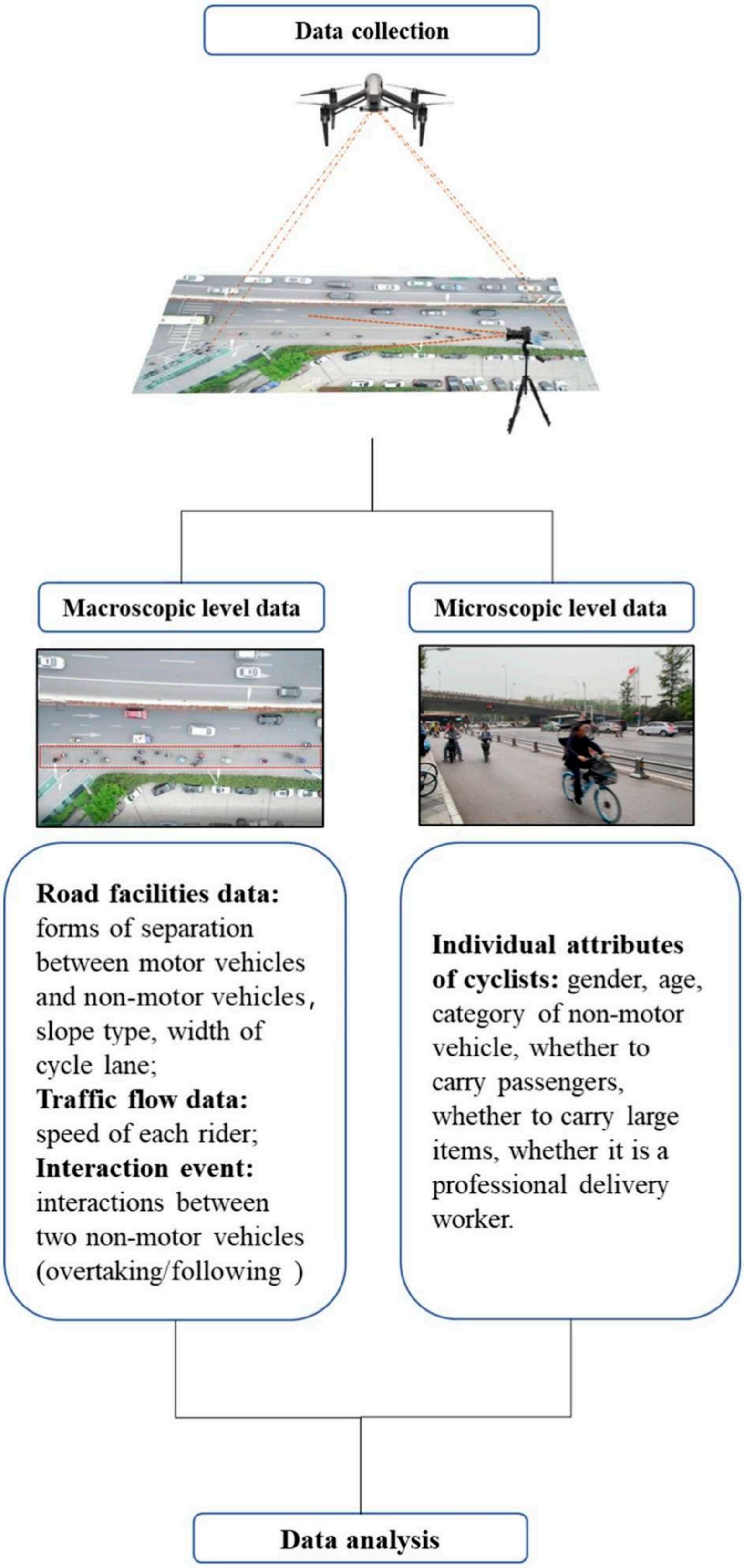
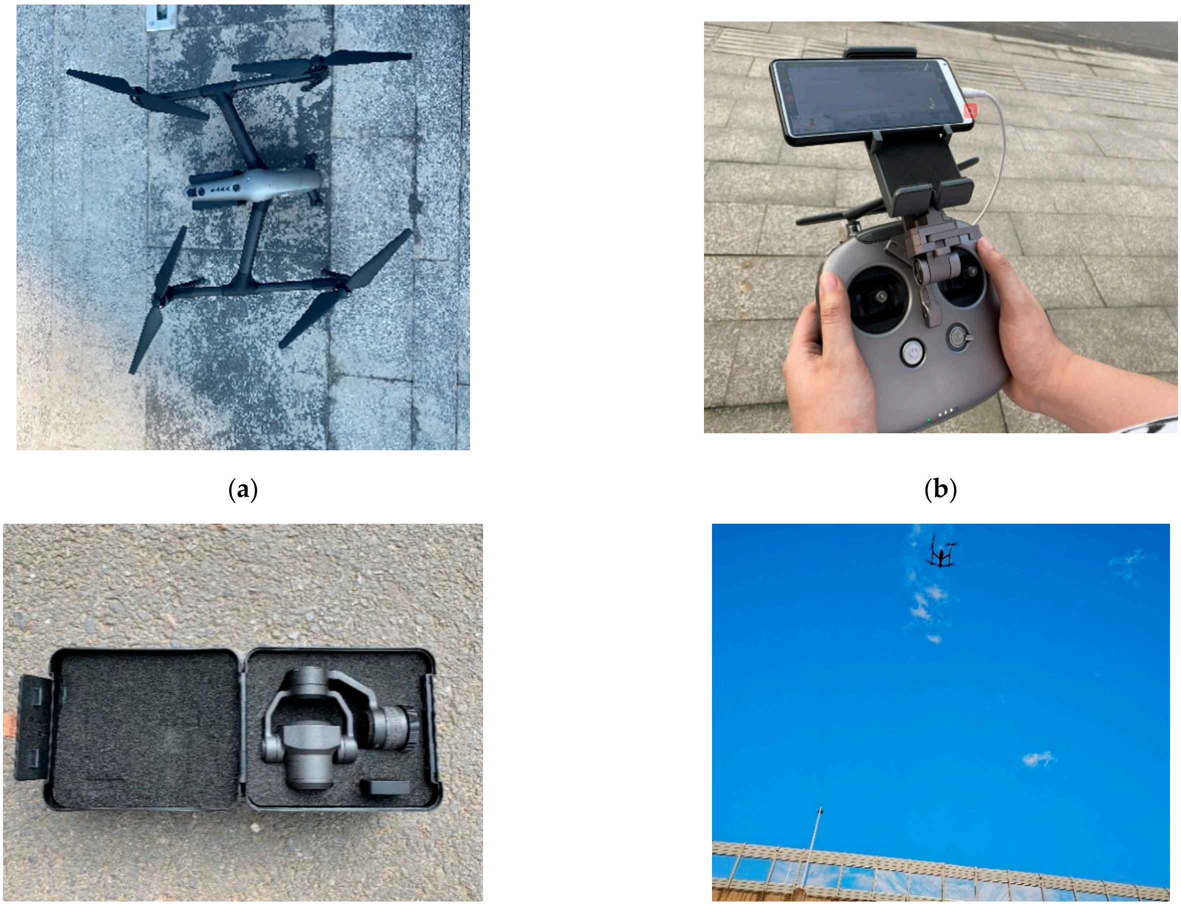


Figure 1. Methodology scheme.



(**a**) (**b**)

(**c**) (**d**)

Figure 2. Unmanned aerial vehicle equipment composition and aerial scene. (**a**) DJI Drone Inspire 2; (**b**) wireless transmission image monitoring; (**c**) 360° ultra-clear pan-tilt camera; (**d**) drone aerial photography scene.

Figure 3. Roadside camera at a static position.

Table 1. Description of segments characteristics.

Road Segment No.	Location	Geometrical Characteristic	Road Segment Length (m)	Road Segment Width (m)	Boundary Attribute
Segment 1	North Side of Nanxunmen Bridge, South First Ring Road	Straight line segment	65.6	3.2	Greening isolation
Segment 2	Changjiang Middle Road	Straight line segment	61.6	3.5	Greening isolation
Segment 3	Huizhou Boulevard Melo City	Straight line segment	58.7	3.2	Greening isolation
Segment 4	Huizhou Boulevard Qingnian Road Primary School	Straight line segment	57.3	3.8	Greening isolation
Segment 5	Wuhu Road Baohe Wanda	Straight line segment	57.6	5.2	Fence isolation
Segment 6	Ma'anshan Road Westin	Uphill segment	66.4	3.4	Fence isolation
Segment 7	Dadongmen Shengli Bridge	Downhill segment	58.4	5.2	Fence isolation
Segment 8	Huizhou Boulevard Qingnian Road Primary School	Straight line segment	67.8	3.9	Greening isolation
Segment 9	South First Ring Shuguang Bridge	Straight line segment	65.3	2.7	Fence isolation
Segment 10	Huaining Road Block 1912	Straight line segment	50.8	2.8	Fence isolation
Segment 11	Dadongmen Shengli Bridge	Uphill segment	59.5	3.9	Fence isolation
Segment 12	Ma'anshan Road	Downhill segment	65.8	3.4	Fence isolation

There were three members of the research team at the scene: one member controlled the drone, one took care of the roadside camera, and one took on the auxiliary work. The researchers first debugged and prepared the equipment, set up the roadside camera, and adjusted the angle when the drone reached a reasonable height. Then, the video recording buttons of the drone and the roadside camera were pressed at the same time to ensure that the video taken by the drone and the video taken by the camera corresponded to each other during the later data-processing stage. After the shooting, the researchers measured and recorded the width, length, and other data from the survey road segment.

2.3. Data Extraction and Processing

The speed data are extracted using Simi Motion software and manual punctuation. The steps are as follows:

Step one: Video import. The video taken by the drone is converted into a format readable by Simi Motion software 9.2.1 (Simi Reality Motion Systems GmbH, Munich, Germany) by format factory software, and then imported into the Simi Motion software.

Step two: Image calibration. According to the measured distance in the traffic investigation, the pixel distance of the video is calibrated. Using the four-point calibration method, four points of 1, 2, 3, and 4 are selected as marking points, and the actual measured distances of 1–2 and 2–3 are input to complete the image calibration of the video, as shown in Figure 4.

Step three: Non-motorized vehicle tracking. Manual dotting is used to mark the center point of a non-motorized vehicle as a tracking mark point. If the mark point is separated from the vehicle in the process of automatic software follow-up, it is necessary to interrupt and re-mark it from the current moment, and then continue tracking until the marker disappears from the video. After all of the videos are tracked, the results are saved to obtain the position of each non-motorized vehicle in each frame relative to the initial coordinate origin, as shown in Figure 4.

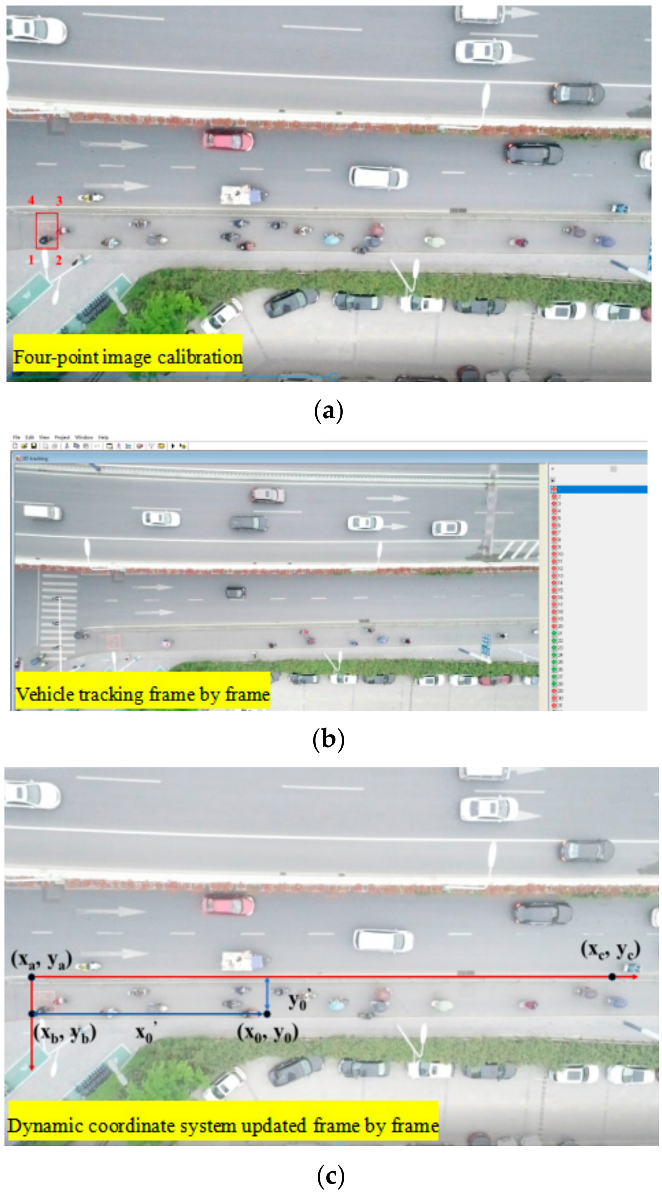


Figure 4. Video data extraction process. (**a**) Four-point image calibration; (**b**) Vehicle tracking frame by frame; (**c**) Dynamic coordinate system updated frame by frame (the red and blue lines have constructed a coordinate system).

Step four: Video correction. To stabilize the video shoot, the traffic survey is conducted at a time when the weather is fine and there is no wind. Moreover, DJI drones boast strong hover-shooting stability and satisfactory image anti-shake effect, but the video still has slight jitter at a certain angle. To obtain more accurate data, the initial coordinates of each frame obtained in step three are projected along the non-motorized vehicle lane line and the vertical direction, and the XOY coordinate system is constructed, with the X axis along the non-motorized vehicle lane direction and the Y axis in the vertical direction. In the video tracking stage, three fixed points in the image are selected, as shown in the figure. The coordinates are respectively calibrated as (x_a, y_a), (x_b, y_b), (x_c, y_c), and then the new coordinates (x_0', y_0') of non-motorized vehicles at the current moment can be obtained via coordinate conversion, as shown in Formula (1).

$$\begin{cases} {x_0}' = \dfrac{\frac{y_b - y_a}{x_b - x_a}(x_a - x_0) + (y_0 - y_a)}{\sqrt{1 + (\frac{y_b - y_a}{x_b - x_a})^2}} \\ {y_0}' = \dfrac{\frac{y_c - y_a}{x_c - x_a}(x_a - x_0) + (y_0 - y_a)}{\sqrt{1 + (\frac{y_c - y_a}{x_c - x_a})^2}} \end{cases} \tag{1}$$

Step five: Data smoothing. To reduce the random fluctuation of space–time coordinates during vehicle tracking, the five-point difference method is used to smooth the coordinates of non-motorized vehicles, as shown in Formula (2). For example, after the coordinate information of non-motorized vehicles is obtained, the first derivative of the coordinates will give the speed of each non-motorized vehicle at every moment, as shown in Formula (3).

$$(x_i, y_i) = \frac{(x_{i-2}, y_{i-2}) + (x_{i-1}, y_{i-1}) + (x_i, y_i) + (x_{i+1}, y_{i+1}) + (x_{i+2}, y_{i+2})}{5} \tag{2}$$

$$\begin{cases} v_{ix}(t) = (x_i(t + \Delta t) - x_i(t - \Delta t)/2\Delta t \\ v_{iy}(t) = (y_i(t + \Delta t) - y_i(t - \Delta t)/2\Delta t \end{cases} \tag{3}$$

where:

$x_i(t)$—longitudinal position of a bicycle *i* at time *t*;
$y_i(t)$—lateral position of a bicycle *i* at time *t*;
$v_{ix}(t)$—longitudinal position of a bicycle *i* at time *t*;
$v_{iy}(t)$—lateral position of a bicycle *i* at time *t*.

After the above extraction process, the coordinates and speed information of each vehicle can be obtained. For the extraction of microscopic individual indicators, the manual information identification and recording method of professionals is adopted. In this study, eight graduate students were assigned to perform this work. Prior to information discrimination, information identification training should be carried out for recorders, and unified standards should be established in identifying different vehicle types, judging individual attributes of riders, and how distinguishing information quickly and accurately. Each road segment is equipped with two graduate students to ensure accurate and efficient data recording. By processing the data of 12 road segments separately, the following indicators can be obtained statistically, which lays the foundation for the follow-up research.

Speed: The distance traveled by vehicles in a unit of time. The average speed of the whole road segment is the arithmetic average of the speeds of all types of non-motorized vehicles on the non-motorized vehicle lane, which can reflect the average state of non-motorized vehicles on this road segment.

Interaction events: The overtaking/car-following interaction is observed between two non-motorized vehicles according to the video. According to previous studies, when the longitudinal distance between two vehicles involved in an interactive event is less than 5 m, it is recorded as an interactive event, and it is determined whether this interactive behavior is overtaking or following [25]. The individual attributes of the overtaking vehicle and the overtaken vehicle should be identified from the camera.

Individual attributes of riders: judge the individual attributes of riders, gender (male/female), age (young/middle-aged/elderly), category of non-motorized vehicles (as shown in Figure 5), human-carrying/large object-carrying, and professional delivery personnel such as courier/takeaway rider.

2.4. Data Analysis

In this study, the rider's decision in overtaking behavior is taken as the dependent variable, and its values are binary, Y = 0, which indicates that the non-motorized vehicle rider chooses to follow the car, and Y = 1 indicates that the non-motorized vehicle rider chooses to overtake. The binary logit model shows strong adaptability in dealing with the situation that such dependent variables are binary variables.

(**a**) (**b**) (**c**)

Figure 5. Primary types of non-motorized vehicles: traditional bicycle (**a**), electric bicycle (**b**), and human-powered tricycle (**c**).

A binary logit regression model was estimated to model the overtaking decision of non-motorized vehicle riders:

$$\text{logit}(p) = \log(\frac{p}{1-p}) = \beta_k x_{kn} + \varepsilon_{kn}$$

where X_{kn} is the vector of explanatory variables, β_k is the vector of corresponding coefficients for explanatory variables, and ε_{kn} is the identically and independently distributed random error term.

At the same time, the influence parameter coefficient was assumed to be random distribution, considering that the heterogeneity of the variables was not observed [32,33].

$$\beta_{kn} = \beta'_n + \varphi_{kn}$$

where β'_n is the mean effect of the variable, and φ_{kn} represents normal distribution with the means of zero and variances of σ^2.

Therefore, the overtaking probability of the rider's random parameter logit model is constructed as:

$$\text{Prob}[y_k = 1|x_k, \beta_k] = F(\beta'_k x_k)$$

To determine whether a variable could be selected as a random parameter, a stepwise iterative method was established [34]. Every variable was evaluated in the model as a fixed or a random parameter. A statistical test of improved likelihood was used to determine the fitness. These processes continued until the model was stable to the change, and the model fit best.

In the present study, the variables 'Age' and 'Whether it is a professional delivery worker' were selected as random parameters. Hence, normal/lognormal/uniform distributional forms were tested, and the simulated maximum likelihood with 200 Halton draws was used to make the coefficient estimation computationally efficient. As a result, the normal distribution provided the best estimation results. The Akaike information criterion (AIC) was used to evaluate the fitting performance of the candidate models. The NLOGIT 5.0 statistical software (Econometric Software Inc., Greene, 2012) was used in the analysis.

3. Results

To investigate the overall speed characteristics and individual differences of non-motorized vehicles, this paper extracts 30-min video data of each of the 12 road segments and uses the method described in Section 2.3 to identify the individual information of each cyclist, with a total of 8908 samples. The average speed of all individuals is 5.56 m/s (SD = 2.213), the minimum speed is 0.02 m/s, the maximum speed is 16.04 m/s, the 85% percentile speed is 7.75 m/s (27.9 km/h), and the 75% percentile speed is 6.94 m/s (24.98 km/h). Therefore, in the mixed flow of bicycle lanes, there are large differences between various types of vehicles, with electric bicycles being faster and more flexible than traditional bicycles. The overtaking phenomenon is one of the main characteristics of mixed non-motorized vehicle traffic flow. Overtaking behavior will cause interference to overtaken vehicles and other vehicles nearby, and will have a certain negative impact on the safe operation of traffic flow in non-motorized vehicle lanes.

Generally speaking, the number of overtaking events has a close bearing on the traffic volume on non-motorized vehicle lanes and fluctuates with the change in traffic volume. The overtime rate is the number of successful overtaking times of non-motorized vehicles with overtaking behavior per unit time compared with the total number of non-motorized vehicles passing by per unit time. This index fluctuates less with the change in traffic volume, which is more suitable for describing overtaking conflicts on non-motorized vehicle lanes. The overtime rate of each road segment is shown in Table 2.

Table 2. Overtaking rates of road segments.

Road Segment No.	**Segment 1**	**Segment 2**	**Segment 3**	**Segment 4**	**Segment 5**	**Segment 6**
Overtaking rate	19.2%	12.3%	19.5%	5.5%	18.2%	18.2%
Road Segment No.	**Segment 7**	**Segment 8**	**Segment 9**	**Segment 10**	**Segment 11**	**Segment 12**
Overtaking rate	24.5%	10.2%	15.1%	5.9%	12.5%	22.7%

3.1. Basic Characteristics

According to the survey video, the following overtaking phenomena occur in the mixed non-motorized vehicle traffic flow: overtaking of traditional bicycles by light-friction electric bicycles, overtaking of ordinary electric bicycles by light-friction electric bicycles, overtaking of light-friction electric bicycles by light-friction electric bicycles, overtaking of human-powered tricycles by light-friction electric bicycles; overtaking of traditional bicycles by ordinary electric bicycles, overtaking of ordinary electric vehicles by ordinary electric vehicles, overtaking of light-friction electric vehicles by ordinary electric vehicles, overtaking of human-powered tricycles by ordinary electric vehicles; overtaking of traditional bicycles by traditional bicycles, overtaking of ordinary electric bicycles by traditional bicycles, overtaking of human-powered tricycles by traditional bicycles; overtaking of traditional bicycles by human-powered tricycles, overtaking of ordinary electric bicycles by human-powered tricycles, overtaking of light-friction electric vehicles by human-powered tricycles. On the non-motorized vehicle lanes where the vehicles are not physically isolated, overtaking decisions are influenced by the geometric characteristics of the road and the characteristics of the riders. This study extracts 940 close-range interactive events and considers the influencing factors of overtaking decisions from the two aspects of the geometric characteristics of the road and the individual differences of the riders. Table 3 makes descriptive statistics of various elements in interactive events, and it can be found that there are slightly more women than men, young and middle-aged people are the main body, and electric bicycles account for the largest proportion. Nearly 12% of the participants have the phenomenon of human-carrying/large object-carrying, and the professional delivery staff group accounts for 18.6% of the survey population.

In this study, the dependent variable "whether to overtake or not" is a binary variable, and the ratio of P of the event to *1-P* of the probability of not happening is the odds ratio, also known as OR value. It means that when the independent variable X_k changes by one unit, the corresponding OR value of the dependent variable changes $EXP(\beta_k)$ units on average, with other independent variables unchanged. In the binary logit model, the influence of influencing factors on dependent variables is mainly judged according to the OR value and 95% confidence interval. When the OR is equal to 1, this factor does not affect overtaking behavior; if the OR value is greater than 1, this factor will increase the probability of overtaking; if the OR value is less than 1, this factor will reduce the occurrence of overtaking behavior. Therefore, this study divides the rider's overtaking decision y_k into two categories: when $y_k = 0$, it means that the rider (k) closely followed the preceding car and did not overtake; when $y_k = 1$ it means that the rider (k) overtook the preceding vehicle.

Table 3. Descriptive statistical analysis.

Variable	Category	Overtaking or Not		Total
		0	1	
Gender	Female	66.10%	34.22%	52.13%
	Male	33.90%	65.78%	47.87%
Age	Young people	31.44%	40.05%	35.21%
	Middle-aged people	54.55%	56.31%	55.32%
	Elderly people	14.02%	3.64%	9.47%
Non-motorized vehicle type	Traditional bicycle	21.97%	6.07%	15.00%
	Electric bicycle	66.29%	78.16%	71.49%
	Human-powered tricycle	11.74%	15.78%	13.51%
Human-carrying/large object-carrying?	No	88.83%	87.62%	88.30%
	Yes	11.17%	12.38%	11.70%
Professional delivery personnel?	No	86.36%	75.00%	81.38%
	Yes	13.64%	25.00%	18.62%
Isolation mode	Fence isolation	71.21%	68.69%	70.11%
	Greening isolation	28.79%	31.31%	29.89%
Slope type	Straight line segment	75.38%	63.35%	70.11%
	Uphill segment	13.64%	11.41%	12.66%
	Downhill segment	10.98%	25.24%	17.23%
Type of vehicle being overtaken	Traditional bicycle	6.25%	11.89%	8.72%
	Electric bicycle	89.58%	85.44%	87.77%
	Traditional bicycle	4.17%	2.67%	3.51%

Gender, age, type of non-motorized vehicles, human-carrying/large object-carrying, professional delivery personnel or not, type of non-motorized vehicles being overtaken/followed, isolation mode, slope type, and width of non-motorized vehicle lanes are set as independent variables, and whether overtaking is set as dependent variables, to explore the influence of independent variables on dependent variables. Variables are assigned to the above nine influencing factors, as shown in Table 4. In model building, multi-category variables will be converted into dummy (dummy) variables. If dummy variables have k categories, they will be converted into $k - 1$ types, and one of them will be selected as a reference variable for analysis. The variables are classified into two categories and are assigned to 0 and 1.

3.2. Multicollinearity Diagnostics

To avoid the multicollinearity among several influencing factors adversely affecting the accuracy of the model results, a multicollinearity test of the influencing factors is needed. As shown in Table 5, the results of the multicollinearity test show that the independent variable tolerance in this paper is much higher than 0.1, and the variance inflation factor (VIF) is less than 5, which indicates that there is no potential multicollinearity among the influencing factors of the above choices, and it can be used for subsequent analysis.

3.3. Overtaking Probability of Riders' Random Parameter Logit Model

Table 6 shows that gender has a significant positive influence on the overtaking behavior of riders at a 1% significance level. Among them, the probability of male riders choosing overtaking behavior is 5.204 times that of female riders (β = 1.649, OR = 5.204).

Table 4. Variable assignment and explanation.

Influencing Factor	Variable	Instructions	Mean	Standard Deviation
Gender	x_1	Divided into: male and female, with values of 1 and 0, respectively.	0.479	0.500
Age	x_2	Divided into: young people, middle-aged people, and elderly people, with values of 1, 2, and 3, respectively.	1.743	0.617
Non-motorized vehicle type	x_3	Divided into: traditional bicycles, electric bicycles, and human-powered tricycles, with values of 1, 2, and 3, respectively.	1.985	0.534
Human-carrying/large object-carrying?	x_4	Divided into: Yes and No, with values of 1 and 0, respectively.	0.117	0.322
Professional delivery personnel?	x_5	Divided into: Yes and No, with values of 1 and 0, respectively.	0.186	0.389
Isolation mode	x_6	Divided into: fence isolation and greening isolation, with values of 0 and 1, respectively.	0.299	0.458
Slope type	x_7	Divided into: straight line segment, uphill segment, and downhill segment, with values of 1, 2, and 3, respectively.	1.471	0.771
Width of non-motorized vehicle lane	x_8	2.7–5.2 m	3.775	0.926
Types of bicycles being overtaken/followed	x_9	Divided into: traditional bicycles, electric bicycles, and human-powered tricycles, with values of 1, 2, and 3, respectively.	1.948	0.346

Table 5. Result of multicollinearity test.

Variable	Collinearity Statistics	
	Tolerance	Variance Inflation Factor
Gender	0.970	1.031
Age	0.979	1.021
Non-motorized vehicle type	0.959	1.043
Human-carrying/large object-carrying?	0.986	1.014
Professional delivery personnel?	0.967	1.034
Isolation mode	0.745	1.342
Slope type	0.462	2.163
Width of non-motorized vehicle lane	0.544	1.839
Types of bicycles being overtaken/followed	0.974	1.026

Non-motorized vehicle types have a significant impact on the overtaking behavior of riders at a 1% significance level. The results show that electric bicycles (β = 1.699, OR = 5.466) and human-powered tricycle riders (β = 1.523, OR = 4.587) choose to overtake more frequently than ordinary riders.

Similarly, the type of non-motorized vehicle in front of the rider will also have a significant impact on his overtaking behavior choice. The probability of riders choosing overtaking behavior when the front non-motorized vehicles are electric bicycles and human-powered tricycles is 0.389 times (β = −0.945, OR = 0.3894) and 0.343 times (β = −1.069, OR = 0.343) that when the front non-motorized vehicles are traditional bicycles.

The width of non-motorized vehicle lanes has a significant positive impact on the overtaking behavior of riders at a 1% significance level. Every time the width of a non-motorized vehicle lane increases by one unit, the probability of the rider choosing overtaking behavior increases 2.472 times.

The rider's age, at a 1% significance level, also shows negative significance in overtaking behavior choice. The overtaking behavior of young riders (β = 1.353, OR = 3.868) and middle-aged riders (β = 0.895, OR = 2.446) is 3.868 times and 2.446 times that of elderly riders, respectively.

Table 6. Estimation results of random parameter binary logit model.

Factor			Coefficient	Standard Error	Z-Value	Odds	95% Confidence	
							Lower	Upper
Constant			−6.252 ***	0.602	−10.380		−7.432	−5.072
Gender			1.649 ***	0.165	9.990	5.204	1.326	1.973
Type of non-motorized vehicle	Electric bicycle		1.699 ***	0.269	6.300	5.466	1.171	2.227
	Human-powered tricycle		1.523 ***	0.316	4.820	4.587	0.904	2.142
	Traditional bicycle		Control group					
Type of front vehicle	Electric bicycle		−0.945 ***	0.292	−3.240	0.389	−1.518	−0.373
	Human-powered tricycle		−1.069 **	0.504	−2.120	0.343	−2.058	−0.081
	Traditional bicycle		Control group					
Width of non-motorized vehicle lanes			0.905 ***	0.097	9.300	2.472	0.714	1.096
Age (control group: elderly people)	Young people	Mean	1.353 ***	0.276	4.900	3.868	0.811	1.894
		Variance	2.673 ***	0.272	9.830		2.140	3.206
	Middle-aged people	Mean	0.895 ***	0.265	3.380	2.446	0.376	1.413
		Variance	2.270 ***	0.203	11.180		1.872	2.668
Professional delivery personnel?		Mean	0.727 ***	0.200	3.630	2.069	0.335	1.119
		Variance	2.271 ***	0.326	6.960		1.631	2.911
Goodness-of-fit	AIC		1052.8					
	Number of observations		940					
	Unrestricted log-likelihood		−513.38					
	Restricted log-likelihood		−517.014					
	Chi-square statistics		7.27					

Notes: *** Statistically significant at 1% level. ** Statistically significant at 5% level.

In addition, whether the rider is a delivery person or not also significantly affects the choice probability of overtaking behavior. The probability of professional delivery personnel choosing overtaking behavior is 2.069 times that of non-professional delivery personnel (β = 0.727, OR = 2.069).

4. Discussion

In this paper, 12 typical non-motorized vehicle lanes in Hefei, China, are taken as research objects. Through the UAV aerial photography and roadside cameras, non-motorized vehicle running videos are obtained. The data are extracted using Simi Motion 9.2.1(Simi Reality Motion Systems GmbH, Munich, Germany), and manual counting, and the basic data such as overtaking behavior, the individual information of riders, and geometric design parameters of the roads are obtained. On this basis, the logit regression model with random parameters is used to estimate the unobserved heterogeneity and the choice of overtaking behavior of non-motorized vehicles.

4.1. Gender

Male riders are significantly associated with more frequent overtaking behavior. Similar to the results obtained for motor vehicle drivers, the riding speed of male riders is significantly higher than that of female riders, and male riders show more aggressive riding behaviors and are more likely to take the lead than female riders [35–38], all of which make it easier for male riders to choose to overtake during riding. In addition, compared with male riders, females perceive more traffic scenes and riding behaviors with potential risks, which will significantly reduce their willingness to choose overtaking behaviors [39–41].

Inappropriate overtaking behavior can easily lead to road traffic accidents. Feng et al. also found that crashes during overtaking account for approximately 40% of all cyclist roadway fatalities in the United States [42]. Therefore, it is helpful for male riders to make the correct riding decisions when facing different risk riding scenes by improving their cognitive level of the scene risks and objectively and accurately evaluating their own riding ability [43].

4.2. Types of Non-Motorized Vehicles and Types of Lead Non-Motorized Vehicles

There is also a significant correlation between the types of non-motorized vehicles and the overtaking behavior of riders. Among them, electric bicycle riders have the highest probability of overtaking, followed by human-powered tricycle riders and, finally, traditional bicycle riders. There are significant differences in the average speeds of different types of non-motorized vehicles, and compared with traditional bicycles, electric vehicles and human-powered tricycles travel faster [1,44]. To pursue a smoother travel experience, electric bike and human-powered tricycle riders will constantly overtake the low-speed vehicles ahead. Compared with traditional bicycles, electric bicycles have more advantages and are more favored by people, such as increased travel distance, making it easier to stop and accelerate, and overcoming challenging terrain and other obstacles. However, Yeung et al. and Qian et al. found that electric bicycles and human-powered tricycles are associated with a higher risk of injury and a more serious degree of injury [45–47]. Therefore, the implementation of stricter driving requirements, management regulations, and higher penalties for illegal activities for electric bicycle and human-powered tricycle riders will help to ensure the safety of non-motorized vehicle travel, such as forcing electric bicycle riders to use helmets and imposing fines for riding without helmets.

Similarly, Table 6 also shows that the type of non-motorized vehicle in front of the rider will also have a significant impact on their overtaking behavior choice. Among them, the probability of overtaking is the highest when the vehicle in front is a traditional bicycle, followed by a human-powered tricycle, and, finally, an electric bicycle. This is also because when the front non-motorized vehicle is running too slowly and lower than its expected speed, riders often choose to overtake the front vehicle in order to maintain their normal driving. Among them, the speed of the overtaken vehicle is the controlling factor that determines the overtaking time and the difficulty of overtaking. When the speed difference between the two vehicles is high, the faster one can easily overtake the slower one in a short time [48]. Barmpounakis et al. also found that the most important factor affecting the overtaking behavior of non-motorized vehicle drivers is the speed difference with the preceding vehicle, followed by the speed of non-motorized vehicles [49].

4.3. Width of Non-Motorized Vehicle Lanes

The probability of overtaking behavior of riders on wider non-motorized vehicle lanes is greater than that on narrower non-motorized vehicle lanes [50]. Generally, non-motorized vehicle riders should not only have overtaking motivation (such as a large speed difference between the front and rear vehicles), but also meet the overtaking conditions, that is, there is enough lateral overtaking clearance. In the case of a wider non-motorized vehicle lane width, the higher the overtaking affluence is, and the easier it is for the rider to finish overtaking. In the case of a narrower non-motorized vehicle lane width, the rear vehicle needs to overtake the front vehicle with a relatively small lateral gap. At this time, overtaking may cause great interference to the rider in the front vehicle. Furthermore, riders who have been overtaken may still feel unsafe and uncomfortable because they instinctively want to stay away from a high-speed, high-weight object. In this case, they may act to hinder the overtaking of the rear vehicle [51].

4.4. Age

Age is normally distributed, with standard deviations of 2.673 for young people and 2.270 for middle-aged people. The results indicate that 69.5% of the distribution is greater than 0 for young people and 65.17% of the distribution is greater than 0 for middle-aged people, which means that young and middle-aged people are associated with a higher probability of overtaking behavior. Young riders are inexperienced in riding, but they are more adventurous and have a strong sense of speed, which leads them to choose frequent overtaking behaviors [52]. However, with the increase of age, the probability of overtaking behavior decreases significantly. This may be because the older riders' ability to control non-motorized vehicles and their ability to perceive the risks of the external environment will decrease and the riding risks will increase significantly, especially for older riders. In this case, they tend to slow down and reduce overtaking frequency to make up for this risk. Schepers and Brinker also found that the oldest riders generally have poorer eyesight, longer reaction times in traffic conditions, and higher riding risk [52]. Even so, studies have found that the youngest (less than 18 years old) and oldest (over 65 years old) riders are more likely to be involved in fatal accidents than other age groups [53]. Currently, almost all non-motorized vehicle riders are self-taught, lacking proper driving education or training, and their riding abilities are uneven. Riders may even accumulate experience through trial and error, and often ignore the importance of the concept of safe riding [43]. Therefore, for young riders, attention should be paid to the training of their riding skills and risk perception, so as to help them evaluate their riding ability truly and accurately [54]. For elderly riders, protection measures for elderly riding should be taken, and correct cognition should be cultivated, such as wearing helmets and regular physical examinations such as vision examinations. The publicity of traffic rules and strengthening of punishment measures are also common means to ensure riding safety.

4.5. Whether Riders Are Professional Delivery Personnel

Whether the riders are professional delivery personnel is normally distributed, with standard deviations of 0.727. The result shows that 62.55% of the distribution is greater than 0, which indicates that a professional delivery rider is associated with a higher probability of overtaking behavior. For professional delivery personnel, time pressure is a key issue, because they need to complete the order distribution within a short time, otherwise there will be fines and complaints from customers [55,56]. Therefore, they are in more of a hurry compared with other non-professional delivery riders. According to relevant research, professional delivery personnel are often found to have abnormal riding behaviors (overtaking at high risk, whistling all the time, etc.) and violate traffic rules, such as speeding, driving in the opposite direction, and running red lights [57–59]. For this reason, the supervision of the illegal and high-risk traffic behaviors of professional delivery personnel should be strengthened, and their income distribution and reward and punishment methods should be improved.

5. Conclusions and Limitation

Non-motorized vehicles are the most environmentally friendly means of transportation, and have become increasingly popular. The increase in the number of non-motorized vehicles has also led to an increase in related collisions year by year. Overtaking behavior is one of the important causes of collisions involving non-motorized vehicles. The studies on the influencing factors of non-motorized overtaking behavior have not been deeply explored. Therefore, as the main contribution, this study provided insights into the significant factors affecting riders' overtaking behavior in China. A drone inspire was used to collect riders' individual characteristics, road attributes, and naturalistic riding behaviors. The random parameter logit regression model was used to estimate the unobserved heterogeneous characteristics and the riders' overtaking behaviors.

More specifically, the significant overtaking behavior predictors from the model included gender, type of the non-motor vehicle ahead, the width of the non-motor vehicle lane, age, and whether the rider is a professional deliverer. There is an interesting finding that professional delivery riders are more likely to choose more frequent overtaking behavior. At present, the growing demand for delivery services has led to more and more professional delivery riders. As their riding behaviors have a serious impact on other road users, regulating their riding behavior is particularly important for road safety. Therefore, a stricter standard that applies to professional delivery riders and a stronger penalty for illegal riding behavior should be formulated to reduce the occurrence of non-motorized vehicle accidents. In addition, safety education and riding behavior training exercises on a regular basis are also necessary. Taken together, the findings of this study can provide theoretical and methodological support for the formulation of non-motor vehicle control measures.

Nonetheless, some limitations still exist in this paper. For one thing, the observation data of this study only come from Hefei, and the amount of data is limited. In the future, observation data can be collected from other cities to verify and improve the research results. Secondly, the road segments selected in this study are non-separated road segments, rather than mixed-use road segments, where traffic vehicles interweave and interfere with each other seriously, and the riding behavior of riders on non-mixed road segments is more complicated. In this case, whether the factors that affect the choice of overtaking behavior will change or not remains to be explored. In the future, more diverse non-motorized riding scenes can be selected to improve the universality of the research results. In addition to the effects of cyclists' characteristics and the infrastructure environment, further factors such as time variation, low illumination, weather, the surrounding landscape, and trajectory-based parameters may also affect overtaking behaviors. In the present research, the influence of inherent properties on overtaking behavior were considered. In the future, we will focus on analyzing the variables and parameters based on the cycling trajectory from a more microscopic perspective, taking the trajectory research and traffic simulation of motor vehicles as references [60–62], and consider the overtaking behavior of non-motor vehicles from the perspective of mathematical models.

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