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Machine Learning-Based Intention Recognition for Right-Turning Vehicles at Signalized Intersections

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Abstract: Signalized intersections serve as critical hubs in urban road networks. At intersections without dedicated right-turn phases, frequent interactions occur between right-turning vehicles and pedestrians/non-motorized vehicles. Suboptimal interactions may lead to traffic conflicts, significantly compromising travel safety and operational efficiency. This study categorizes right-turning vehicle intentions into three types: full-stop yielding, deceleration yielding, and non-yielding behaviors. Influencing factors are classified into agent-related factors and environmental factors, with input features for intention recognition models being selected through filter methods. Three intention recognition models-Support Vector Machine, Random Forest, and Logistic Regression-are developed to identify right-turning vehicle intentions. Through comprehensive evaluation metrics including accuracy and precision, comparative analysis reveals that the Logistic Regression model demonstrates optimal overall performance in precisely capturing right-turning vehicle intentions.

1. Introduction

Numerous studies have investigated right-turning vehicle behaviors at signalized intersections. Ankriti [1] enhanced pedestrian social force models by treating vehicles and pedestrians as right-of-way entities, employing hybrid calibration methods to reveal an inverse correlation between the action radius of right-of-way entities and interaction intensity. Sheykhfard [2] integrated logistic regression models to demonstrate that countdown timers during signal phase transitions significantly influence driver-pedestrian interactions. Wang [3] developed a vehicle yielding model for right-turn lane capacity evaluation, incorporating pedestrian density, crosswalk length, and signal timing, validated through Monte Carlo simulations. Xiao [4] utilized SHAP (SHapley Additive exPlanations)-interpreted machine learning methods on pedestrian-vehicle collision databases, identifying walking speed, low-speed vehicles, pedestrian volume, and signal cycle length as critical risk factors. Pan [5] quantified post-encroachment time and lane capacity for right-turning vehicles and pedestrians, identifying vehicle gap acceptance and reaction time as key safety parameters. Ali [6] analyzed temporal patterns of non-motorized/vehicle conflicts, revealing peak conflict occurrences during the initial red/green signal phases and heightened lateral aggression in non-motorized traffic. Bettina [7] demonstrated that temporal-spatial segregation between bicycles and vehicles enhances safety, while excessive separation in signal phasing paradoxically increases conflict risks. Georgios [8] identified green-time ratio and cross-bicycle flow as primary factors reducing turning-vehicle capacity. Stipancic [9] employed automated conflict detection across Canadian intersections to classify collision severity, establishing gender and vehicle speed as influential determinants. Van [10] investigated Dutch intersection conflicts, emphasizing the significant impact of bicycle lane width on conflict rates.

Despite existing research, a systematic understanding of right-turning vehicle behaviors at micro-level interactions remains incomplete. To fundamentally decipher the mechanisms governing these behaviors, this study investigates the implicit intentions behind vehicular actions. The spatiotemporal differentiation driven by intention-based interactions constitutes the foundational logic influencing intersection safety and efficiency.

2. Study on Right-Turning Vehicle Behavior and Intention Recognition

2.1. Right-Turning Vehicle Behavior

This study focuses on signalized intersections without dedicated right-turn phases. Interactions between right-turning vehicles and other traffic participants are categorized into two types: right-turning vehicle-pedestrian interactions and right-turning vehicle–non-motorized vehicle interactions.

Pedestrian interactions primarily occur in one scenario: when pedestrians cross the intersection via crosswalks, bidirectional pedestrian flows interact with right-turning vehicles. Non-motorized vehicle interactions include two scenarios: (1) non-motorized vehicles traveling straight in dedicated lanes exhibit partially overlapping or proximate trajectories to right-turning vehicles, resulting in interactions; (2) non-motorized vehicles crossing via crosswalks or adjacent areas interact with right-turning vehicles.

Right-turning vehicle behaviors are classified into three categories based on yielding patterns and acceleration changes:

Deceleration yielding: During interactions, the driver recognizes the interacting party's crossing intent but cannot confidently determine whether the current speed allows safe passage through the interaction zone. The driver reduces speed to yield priority.

Full-stop yielding: During interactions, the driver determines that deceleration alone cannot provide sufficient time for the interacting party to safely pass. A complete stop is executed to grant priority.

Non-yielding: During interactions, the driver asserts right-of-way by maintaining speed, either passing through the interaction zone before the interacting party or compelling them to yield.

2.2. Right-Turning Vehicle Intention Recognition

Right-turning vehicle intentions precede observable behaviors and are categorized into three classes: full-stop yielding intention, deceleration yielding intention, and non-yielding intention.

The input features for the intention recognition model are divided into two categories: agent-related features (vehicle-specific attributes) and environmental features. These encompass multiple sub-features:

$$X = [x_1, x_2, \ldots, x_n] \in \mathbb{R}^N \quad (1)$$

The essence of intention recognition lies in selecting appropriate input features and constructing a mapping function to associate features with intentions:

$$f: \mathbb{R}^N \rightarrow y \quad (2)$$

Three machine learning models—Support Vector Machine (SVM), Random Forest, and Logistic Regression—are employed to establish this mapping. Each algorithm is parameter-optimized to maximize recognition performance. During intention recognition, the model outputs probabilities for all three intention classes, with the highest probability determining the final classification:

$$P(y = k \mid X; \theta) = f_k(X; \theta), k = 1,2,3 \quad (3)$$

Successful recognition is confirmed when the model's prediction matches the ground-truth label.

2.3. Data Collection

Table 1: Data Inventory of Traffic Participant Extraction

Number	Data	Data Type	Remarks
1	Gender of right-turning vehicle driver	Categorical Data	0 = Female; 1 = Male
2	Age of right-turning vehicle driver	Categorical Data	0 = Young; 1 = Middle-aged; 2 = Elderly
3	Energy type of right-turning vehicle	Categorical Data	0 = Traditional fuel vehicle; 1 = New energy vehicle
4	Average speed before right turn (vehicle)	Continuous Data	Unit:m/s
5	Average acceleration before right turn (vehicle)	Continuous Data	Unit:m/s^2
6	Category of interacting object	Categorical Data	0 = Pedestrian; 1 = Bicycle; 2 = Electric bicycle
7	Gender of interacting object	Categorical	0 = Female; 1 = Male

		Data	
8	Age of interacting object	Categorical Data	0 = Young; 1 = Middle-aged; 2 = Elderly
9	Initial speed of interacting object	Continuous Data	Unit:m/s
10	Distance between right-turning vehicle and interacting object	Continuous Data	Unit:m
11	Time period	Categorical Data	0 = Peak hour; 1 = Non-peak hour
12	Shooting location	Categorical Data	Location codes: 0, 1, 2
13	Following scale of pedestrians/non-motorized vehicles	Continuous Data	Unit: number
14	Behavior of right-turning vehicle	Categorical Data	0 = Full-stop yielding; 1 = Deceleration yielding; 2 = Non-yielding

Video data were collected at three signalized intersections, capturing 24 hours of interactions between right-turning vehicles and pedestrians/non-motorized vehicles. Right-turning vehicles were designated as primary agents, while interacting pedestrians and non-motorized vehicles were classified as interaction objects. (Table 1)

To extract high-precision kinematic data (e.g., velocity, acceleration) from video footage, *simition* software (developed by Simi Reality Motion Systems GmbH, Germany) was utilized. This professional motion analysis tool employs advanced tracking algorithms for accurate motion capture. Manual coding supplemented data extraction, including driver demographics (gender,age) constrained by camera angles. Categorical variables (e.g., yielding behavior classification) were manually recorded to minimize subjective bias and ensure data authenticity. The final dataset comprises 342 validated interaction instances.

2.4. Input Feature Study

Feature selection is required prior to constructing machine learning algorithms. Feature selection involves identifying a subset of original features that most significantly influence the target variable. This process aims to reduce dimensionality, minimize noise, and enhance model generalizability. Filter methods in machine learning—a feature selection technique—screen features based on statistical properties before model training. This study preliminarily screens multi-source factors preceding behavioral events and conducts significance analysis with right-turning behaviors to determine input features for intention recognition models.

Based on literature and extracted data, factors influencing interactions are summarized in Table 2. Each factor is analyzed for its relationship with right-turning vehicle behaviors to identify valid input features.

Table 2: Agent-Related and Environmental Factors

First-level Classification	Second-level Classification	Third-level Classification
Agent-related Factors	Pre-right-turn motion status of vehicles	Average speed
		Average acceleration
		Vehicle type (new energy vehicle, traditional fuel vehicle)
	Physiological attributes of drivers	Gender
		Age (young, middle-aged, elderly)
Environmental Factors	Information from interacting objects	Category of interacting objects (pedestrian, bicycle, electric bicycle)
		Initial speed
		Distance
		Gender (of interacting object)
		Age (of interacting object: young, middle-aged, elderly)
		Following scale of interacting objects
		Time period (peak/non-peak hours)
		Size of signalized intersection

Feature selection can be conducted based on the data in Table 3.Factors with p-values > 0.05 (vehicle energy type, interacting object gender/age) show no statistical association with right-turning behaviors and are excluded. Remaining factors ($p< 0.05$) are retained as input features for intention recognition models.

Table 3: Statistical Test Results of Factors

Factors	Test Method	H-value or Chi-square value	P-value
Average speed	Kruskal-Wallis Test	82.21	<0.01
Average acceleration	Kruskal-Wallis Test	64.62	<0.01
Vehicle energy type	Chi-square Test	9.76	0.084
Driver gender	Chi-square Test	15.38	0.032
Driver age	Chi-square Test	21.06	0.027
Category of interacting object	Chi-square Test	48.90	<0.01
Initial speed of interacting object	Kruskal-Wallis Test	53.73	<0.01
Distance between vehicle and interacting object	Kruskal-Wallis Test	69.28	<0.01
Gender of interacting object	Chi-square Test	8.59	0.075
Age of interacting object	Chi-square Test	9.48	0.068
Following scale of interacting objects	Kruskal-Wallis Test	60.05	<0.01
Time period	Chi-square Test	14.33	0.034
Size of signalized intersection	Chi-square Test	12.15	0.041

3. Right-Turning Vehicle Intention Recognition Modeling

3.1. Model Selection

Machine learning, a critical component of artificial intelligence, enables computers to acquire knowledge from complex data and perform predictive or decision-making tasks. Unlike traditional programming, machine learning algorithms autonomously extract deeper patterns from existing data samples through training.

Supervised learning involves datasets with input features and output labels. The algorithm learns the mapping relationship between features and labels to predict new instances. Its defining characteristic is that each input sample has a unique predefined label.

This study addresses a supervised multi-class classification problem for right-turning vehicle intention recognition. Common classification algorithms include K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Naive Bayes, and Decision Trees. Given the relatively small dataset size and structural simplicity, three widely applicable algorithms-SVM, Random Forest, and Logistic Regression-were selected.

3.2. Support Vector Machine Optimized via Simulated Annealing

3.2.1. Algorithm Principle

The Support Vector Machine (SVM) is a supervised learning algorithm based on statistical learning theory, initially designed for binary classification and later extended to multi-class tasks. Its core idea is to identify an optimal hyperplane that maximizes the geometric margin between different classes, ensuring classification accuracy while enhancing generalization.

Assume a training set containing m samples, $\{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}$, where $y_i \in \{+1, -1\}$ denotes class labels. In the feature space, the classification hyperplane is defined by the linear equation $w^T + b = 0$. Here, $w \in R^d$ is the normal vector determining the hyperplane's orientation, and $b \in R$ is the bias term controlling its offset from the origin. The geometric distance from any sample x to the hyperplane is expressed as:

$$r = \frac{|w^T x + b|}{\|w\|} \tag{4}$$

This distance reflects the proximity of the sample to the decision boundary, with larger distances indicating higher classification confidence. To correctly classify all samples, the following constraints must be satisfied:

$$\begin{cases} w^T x_i + b \geq +1, & y_i = +1 \\ w^T x_i + b \leq -1, & y_i = -1 \end{cases} \tag{5}$$

Samples meeting these constraints are termed support vectors, located on the margin boundaries and determining the hyperplane. The sum of distances from two classes of support vectors to the hyperplane constitutes the margin.

The objective is transformed into maximizing the margin under constraints, equivalent to minimizing the squared norm of w:

$$\min_{w,b} \frac{1}{2} \| w \|^2 \tag{6}$$

When samples are linearly inseparable in the original space, SVM introduces the kernel trick to project data into a higher-dimensional space via nonlinear mapping, rendering them linearly separable. The hyperplane equation becomes:

$$w^T \phi(x) + b = 0 \tag{7}$$

Direct computation of inner products in high-dimensional spaces is computationally intensive. Kernel functions implicitly compute these products:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \tag{8}$$

In practice, data often contain noise or slight nonlinearity. Enforcing hard-margin constraints risks overfitting. A soft-margin mechanism is introduced, allowing some samples to violate constraints via slack variables The optimization goal becomes:

$$\min_{w,b,\xi} \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{m} \xi_i \tag{9}$$

Ameter C balances margin maximization and classification error: a larger C prioritizes error reduction (smaller margin), while a smaller C tolerates more errors (larger margin, better generalization). This is implemented via the hinge loss function:

$$\max\left(0{,}1 - y_i(w^T x_i + b)\right) \tag{10}$$

3.2.2. Model Construction

Based on the feature selection results for right-turning vehicles, the filtered features were used as inputs to the Support Vector Machine (SVM) along with their corresponding behavior type labels. The dataset was divided into training and testing sets at an 8:2 ratio.

SVM is inherently a binary classification algorithm. Since this study involves a multi-class classification problem for right-turning vehicle intention recognition—and to avoid classification bias caused by class imbalance in the relatively small dataset—the One-vs-One (OVO) strategy was adopted to extend SVM to a multi-class algorithm.

The choice of SVM kernel function directly impacts model performance. Common kernel functions include the linear kernel, polynomial kernel, and Gaussian kernel. Given the study's characteristics, 5-fold cross-validation (a widely used method suitable for small datasets, which reduces bias from single-fold splitting and provides stable, reliable evaluation for model selection and hyperparameter tuning) was employed to select the kernel type. Among the linear, polynomial, and Gaussian kernels, the Gaussian kernel achieved relatively higher accuracy. Additionally, adjusting its parameters could further enhance model performance, and it required fewer parameters (simplifying tuning difficulty). Thus, the Gaussian kernel was selected as the SVM kernel function.

Parameter tuning for the Gaussian kernel is critical to optimizing model performance. The key parameters C (controlling the model's tolerance for classification errors) and γ (determining the local influence of individual training samples on the decision boundary) were optimized using the Simulated Annealing Algorithm (SAA).

The Simulated Annealing Algorithm is a probabilistic global optimization method inspired by the thermodynamics of solid annealing. Its core mechanism mimics a dynamic equilibrium process of "high-temperature random exploration followed by low-temperature directional convergence" to search for the global optimal solution in the parameter space. The algorithm uses a temperature parameter to control the search process: at high temperatures, it probabilistically accepts inferior solutions according to the Metropolis criterion to avoid local optima; as the temperature decreases gradually following a predefined schedule, the algorithm focuses on local fine-grained search, eventually converging to the global optimal region. By applying SAA to the training set, the optimal parameter combination for C and γ was identified, with results shown in Table 4.

Table 4: Simulated Annealing Optimization Results

model	C	γ
SVM	189.0291	0.02520

Based on the optimization results of the simulated annealing algorithm, the parameters of the support vector machine intention recognition model for right - turning vehicles are set. The final recognition results for the three types of intentions are shown in Table 5.

Table 5: Intention Recognition Results of Support Vector Machine

Intention	Accuracy	Precision
Full-stop yielding intention	0.942	0.904
Deceleration yielding intention	0.937	0.905
Non-yielding intention	0.929	0.885

3.3. Random Forest Optimized by Grid Search Algorithm

3.3.1. Algorithm Principle

Random Forest is a machine learning algorithm based on ensemble learning, widely used in classification and regression tasks. Its core idea is to construct multiple independent decision trees and integrate their prediction results to significantly enhance model generalization and reduce the risk of overfitting caused by single decision trees over-relying on training data details. The algorithm workflow of Random Forest is as follows:

Training Set Generation: Using the Bootstrap method for repeated sampling, construct T independent training sets $(S_1, S_2, \ldots, S_T)$ through random sampling with replacement.

In the decision tree construction process, the algorithm trains a classification model for each training set SS according to the following rules.

During the splitting step, the algorithm randomly selects mm candidate attributes from the total MM attributes to form a local split attribute set.

In the attribute selection step, the construction process calculates the optimal split scheme using the Gini index or information entropy based on the candidate attributes, and then completes the node division.

In the result integration step, the integration method aggregates the classification results of TT decision trees via majority voting, and the model determines the final class of a sample by selecting the class label with the highest frequency.

3.3.2. Model Construction

Based on the feature selection results for right-turning vehicles, the filtered features were used as inputs to the Random Forest along with their corresponding behavior type labels. The dataset was divided into training and testing sets at an 8:2 ratio.

The choice of node splitting method—primarily the Gini index or information gain—was critical. Through accuracy comparison under cross-validation, the Gini index-based node splitting method was found to outperform the information gain method for right-turning vehicle models, so the Gini index was selected as the node splitting criterion.

Key parameters of Random Forest include the number of trees (n_estimators), maximum tree depth (max_depth), and minimum number of samples required to split an internal node (min_samples_split). The grid search algorithm was employed to optimize these parameters. This method involves generating a grid of predefined hyperparameter values, training and validating the model for each parameter combination, and identifying the optimal set. The best-performing parameter combination is shown in Table 6.

Table 6: Optimization Results of Grid Search Algorithm

model	n_estimators	max_depth	min_samples_split
SVM	128	10	12

Based on the grid search optimization results, the parameters of the Random Forest intention recognition model for right-turning vehicles were set. The final recognition results for the three types of intentions are shown in Table 7.

Table 7: Intention Recognition Results of Random Forest

Intention	Accuracy	Precision
Full-stop yielding intention	0.911	0.832
Deceleration yielding intention	0.882	0.846
Non-yielding intention	0.903	0.821

3.4. Logistic Regression Optimized by Bayesian Optimization

3.4.1. Algorithm Principle

Logistic regression, a classic classification algorithm, features a simple structure and strong parameter interpretability, commonly used in binary or multi-class classification tasks. It essentially applies a logistic function transformation to the results of linear regression, mapping outputs to probability values, thus serving as a probabilistic extension of linear models.

The logistic distribution, a type of continuous probability distribution, has its cumulative distribution function and probability density function defined as:

$$F(x) = P(X \le x) = \frac{1}{1+e^{-(x-\mu)/\gamma}} \tag{11}$$

$$f(x) = \frac{e^{-(x-\mu)/\gamma}}{\gamma\left(1+e^{-(x-\mu)/\gamma}\right)^2} \tag{12}$$

Where μ is the location parameter controlling the distribution center, and γ is the shape parameter determining the steepness of the distribution curve.

In logistic regression, the Sigmoid function $g(z)$ is introduced to convert linear combinations into class probabilities. The conditional probability expression is:

$$P(y = 1|x; \theta) = \frac{1}{1+e^{-\theta^T x}} \tag{13}$$

Where θ represents model parameters (feature weights). The specific form of the Sigmoid function is:

$$g(z) = \frac{1}{1+e^{-z}} \tag{14}$$

The linear output part is defined as:

$$h_\theta(x) = \theta^T x \tag{15}$$

3.4.2. Model Construction

Based on the feature selection results for right-turning vehicles, the filtered features were used as inputs to logistic regression along with their corresponding behavior type labels. The dataset was divided into training and testing sets at an 8:2 ratio.

A core goal in model construction is ensuring good predictive performance on unseen data. Overfitting often occurs when model complexity is high or training data is insufficient. Introducing regularization methods can effectively constrain model complexity, balancing fitting accuracy and generalization ability to enhance model stability. This study adopted L2 regularization.

The key parameter to optimize was the regularization parameter C, achieved via the Bayesian optimization algorithm. Bayesian optimization is a global optimization algorithm based on probabilistic models, suitable for scenarios with high objective function computation costs or complex hyperparameter tuning. Its core lies in constructing a probabilistic model of the objective function to intelligently select the next evaluation point. Applying Bayesian optimization to the training set identified the optimal C value, as shown in Table 8.

Table 8: Optimization Results of Bayesian Optimization Algorithm

model	C
LR	6.3×10^{-3}

Based on the Bayesian optimization results, the parameters of the logistic regression intention recognition model for right-turning vehicles were set. The final recognition results for the three types of intentions are shown in Table 9.

Table 9: Intention Recognition Results of Logistic Regression

Intention	Accuracy	Precision
Full-stop yielding intention	0.884	0.821
Deceleration yielding intention	0.894	0.873
Non-yielding intention	0.902	0.871

3.5. Model Performance Summary

A summary of the three models' performance is presented in Table 10.

Table 10: Performance Summary

model	Accuracy	Precision	F1 Score	Sensitivity	Specificity
SVM	0.936	0.931	0.933	0.941	0.935
RF	0.899	0.891	0.895	0.901	0.905
LR	0.893	0.881	0.887	0.895	0.891

SVM: Demonstrated the best overall performance, leading in accuracy (0.936), precision (0.931), and sensitivity (0.941), indicating strong global recognition ability for the three intention classes. RF: Showed moderate performance, with an accuracy (0.899) slightly lower than SVM but a higher specificity (0.905), possibly resulting in fewer misclassifications for negative samples (e.g., "non-yielding intention"). LR: Performed weakest, though with small gaps in all metrics, making it suitable for scenarios with limited computational resources or rapid deployment needs.

Full-stop yielding intention: SVM (0.942) significantly outperformed RF (0.911) and LR (0.884), likely due to SVM's advantage in capturing complex boundaries in high-dimensional feature spaces. Deceleration yielding intention: SVM (0.937) remained leading, while RF (0.882) underperformed, possibly due to insufficient learning of deceleration scenarios from feature interactions. Non-yielding intention: Small differences existed among the three models (SVM 0.929, RF 0.903, LR 0.902), suggesting low feature distinguishability for this class or balanced data distribution.

4. Conclusions

Through a review of existing literature and observations of real-world scenarios, this study comprehensively summarized and analyzed the behaviors of right-turning vehicles, establishing a framework for classifying their intentions based on agent-related and environmental features. By deeply analyzing the relationships between agent/environmental factors and right-turn behaviors, key individual and environmental features critical for intention recognition models were selected. Using these features, three intention recognition models—Support Vector Machine, Random Forest, and Logistic Regression—were developed. Through comprehensive evaluation metrics such as accuracy and F1-score, the SVM model was found to have the best overall performance, enabling precise capture of intentions corresponding to right-turning vehicle behaviors.

References

[1] ANKRITI S, ABHINAV K. Modified social force model for pedestrian–vehicle interactions at a signalized intersection[J]. Transportation Letters, 2024, 16(4): 307-319.

[2] SHEYKHFARD A, HAGHIGHI F, PAPADIMITRIOU E, et al. Exploring the influence of signal countdown timers on driver behavior: An analysis of pedestrian–vehicle conflicts at signalized intersections[J]. Transportation Research Record, 2024, 2678(4): 865-880.

[3] WANG Y, ZHANG X, NAKAMURA H. Left-turn lane capacity estimation based on the vehicle yielding maneuver model to pedestrians at signalized intersections[J]. Sustainability, 2024, 16(6): 1-18.

[4] XIAOQIANG K, SUBASISH D, YUNLONG Z, et al. In-depth understanding of pedestrian–vehicle near-crash events at signalized intersections: An interpretable machine learning approach[J]. Transportation Research Record, 2023, 2677(5): 747-759.

[5] PAN A, ZHANG X, et al. Efficiency and safety evaluation of left-turn vehicles and crossing pedestrians in signalized intersections under the autonomous vehicle mixed flow condition[J]. International Journal of Intelligent Transportation Systems Research, 2021, 20(1): 1-14.

[6] ALI N, GHANI NAA. A comparison of the rank-based and slope-based nonparametric tests for trend detection in climate time series[J]. Applied Mathematics and Computational Intelligence, 2022, 8(2): 123-135.

[7] BETTINA S, SEBASTIAN H, STEFAN H, et al. Determinants of bicycle crashes at urban signalized intersections[J]. Journal of Safety Research, 2023, 87: 132-142.

[8] GEORGIOS G, AXEL L, HEATHER K, et al. Traffic flow at signalized intersections with large volumes of bicycle traffic[J]. Transportation Research Part A: Policy and Practice, 2022, 155: 464-483.

[9] STIPANCIC J, SAUNIER N, et al. Investigating the gender differences on bicycle-vehicle conflicts at urban intersections using an ordered Logit methodology[J]. Accident Analysis & Prevention, 2016, 57: 356-367.

[10] VAN D, GOEDE M D, HAIR-BUIJSSEN S D, et al. Traffic conflicts on bicycle paths: A systematic observation of behaviour from video[J]. Accident Analysis & Prevention, 2014, 62: 358-368.