



Journal of Highway and Transportation Research and Development

Home page: www.sciopen.com/journal/2095-6215



Automatic identification of violations in driver training based on geofence and geospatial analysis

Xin Zhang^{1*}, Shuo Xu¹, Keqi Wu¹, Hui Xiao^{2, 4**}, Huapeng Shen³, Houyong Wang³, Yuanmeng Zhang², Xiaoliang Zhang²

1. Government Service Center of Beijing, Municipal Transport Commission (Beijing Boats Inspection Center), Beijing 100161, China

2. Research and Development Center of Transport Industry of Big Data Processing Technologies and Application for Comprehensive Transport (ZHONG LU GAO KE), Beijing 100088, China

3. Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology, Beijing 100124, China

4. School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China

Abstract: To further improve the regulatory efficiency of the driver training industry and promote the development of “Internet + supervision” in the driver training industry, an off-site supervision method for the driver training industry based on geofence technology and geospatial analysis methods is studied. This method aims to automatically identify and comprehensively supervise whether training vehicles operate in accordance with specified routes and times. Through spatiotemporal matching and spatial mapping of multi-source heterogeneous data such as trajectory data of training vehicles from driving training institutions and geofence data, a multi-source dataset for industry supervision is established. Using the Shapely geospatial analysis library, based on the DE-9IM model, and combined with the multi-source data infrastructure, real-time supervision of training vehicles and automatic identification of violations are realized. The results show that the off-site supervision method proposed in this study can achieve precise supervision of the driving training industry, with a supervision accuracy rate as high as 99.87%. The identification results can serve as an important basis for relevant industry regulatory and law enforcement departments to carry out off-site supervision and early warning in the industry, and promote the intelligent transformation of off-site supervision in the driving training industry.

Keywords: Transportation engineering; traffic supervision; driver training; off-site supervision; geofencing; geospatial analysis; automated detection

1 Introduction

With the rapid development of China’s motor vehicle driver training industry, issues such as low training quality, illegal use of training vehicles, and regulatory loopholes have become increasingly prominent [1]. Traditional supervision relies on manual on-site inspections and self-inspections by enterprises, lacking dynamic management, effective tracking, and collaborative linkage during and after the process [2–3]. To further promote the development of the driver training industry, the *Regulations on the Application for and Use of Motor Vehicle Driving Licenses* clearly states that various emerging technologies represented by artificial intelligence and “Internet +” should be used to promote the digital and intelligent transformation, upgrading, reform, and innovation of the driver training industry. Therefore, how to realize real-time supervision of the driver training industry and improve management quality and efficiency is crucial for enhancing the quality and safety of driver training and strengthening the orderly, healthy, and sustainable development of the industry. In recent years, advances in the Internet of Things, big data, and artificial intelligence have provided technical support for off-site supervision. Compared with traditional inspection methods, off-site supervision achieves pre-

cise management through remote monitoring, data collection, and intelligent analysis [4–5]. *Beijing’s Three-Year Action Plan for Strengthening Off-Site Supervision (2024–2026)* clearly requires the construction of an off-site supervision system for driver training based on video AI analysis and equipment perception.

According to the *Regulations on the Management of Motor Vehicle Driver Training*, motor vehicle driver training institutions conducting training activities on roads must abide by the routes and times designated by the traffic management departments of public security organs. Non-compliance with the designated routes and times for training poses significant risks to traffic safety. However, the traditional on-site supervision model has limited capacity to detect such violations and cannot track vehicle trajectories in real time or collect violation evidence promptly [6]. Therefore, it is urgent to study the off-site supervision application scenario of whether training vehicles adhere to the routes and time limits specified by regulatory authorities, and through intelligent supervision means, develop an off-site supervision model based on AI algorithms to achieve precise targeted supervision, improve the management efficiency and safety quality of the driver training industry, and improve the standardization and safety of driver training services [7].

Received: 30 September 2025; **Revised:** 31 October 2025; **Accepted:** 14 November 2025

* E-mail address: zhangxin1@jtw.beijing.gov.cn; ** Corresponding author: 1520030192@qq.com

DOI: 10.26599/HTRD.2026.9480089

2095-6215/ © The Author(s) 2026. Published by Tsinghua University Press. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

At present, the application of off-site supervision in the transportation industry, such as shipping [8–9], public transportation [10–11], motor vehicle maintenance [12], especially in over-limit and over-load control [13], road-related violation supervision, and transportation source management, has achieved good results. For example: From the perspective of the administrative process theory, Ma [14] analyzed issues with traffic police off-site law enforcement during pre-enforcement preparation, mid-enforcement, and post-enforcement relief stages, and proposed suggestions on following basic requirements such as procedural legitimacy and phased standardized construction; Zhao [15] analyzed the problems and causes of the off-site law enforcement procedures for traffic administrative penalties, and proposed that principles such as the balance of rights and obligations should be followed, and systems should be designed in links such as equipment setup and information review to improve procedures, strengthen legitimacy, and promote law-based administration and rights protection; Chen [16] put forward standardized paths such as strengthening system construction, laying a solid technical foundation, implementing a closed-loop supervision system, and deepening co-governance empowerment, providing an effective plan for the standardization of off-site law enforcement in transportation in the era of artificial intelligence; Sun, et al. [17] proposed optimization methods such as unified identification, double review, and separate penalty responsibility systems to solve procedural problems in off-site traffic law enforcement, which is conducive to protecting the rights of the parties involved and sharing the dividends of remote law enforcement. However, more and more studies have begun to carry out intelligent off-site supervision for the driver training industry. Huang [18] pointed out that in enterprise operation or industry regulation supervision, relevant departments can improve supervision efficiency and promote the further development of related industries by introducing intelligent AI algorithms; Tao, et al. [19] pointed out that it is necessary to deeply integrate the Internet with the driver training industry and build an off-site supervision system for the driver training industry to achieve targeted supervision of the driver training industry; Liang [20] proposed applying cloud platforms to intelligent supervision of the driver training industry to identify problems existing in driver training enterprises, thereby promoting the development of the driver training industry; Li [21] put forward solutions such as improving filing procedures and departmental collaboration, online and offline technical empowerment for collaborative supervision, full-chain dynamic monitoring of training vehicles, and strengthening main responsibilities, which are expected to standardize market access for driver training, realize precise supervision, ensure teaching safety, improve industry service quality, and promote the healthy and orderly development of the driver training market. Although there have been a large number of studies on intelligent supervision of the driver training industry from different perspectives, there are still some deficiencies. Firstly, most existing studies optimize the driver training industry based on public platforms, lacking targeted methods for the driver training industry; secondly, most methods proposed in existing studies rely on on-site supervision models, which cannot meet the current needs of the driver training industry for intelligent development; finally, most current supervision methods mainly focus on pre-event supervision, lacking full-process supervision of the driver training industry.

Based on existing research, this study draws on the development achievements of the Internet of Things, big data, and artificial intelligence technologies, learns from the successful application experience of off-site supervision in transportation fields such as shipping, public transportation, and motor vehicle maintenance, as well as the exploration of intelligent supervision of the driver training industry in existing studies. Aiming at the prominent problems in the current supervision of the driver training industry, such as the lack of targeted methods, reliance on on-site supervision models, and lack of full-process supervision, this study further deepens the

practical path of “Internet + supervision” in the driver training industry. By constructing an off-site supervision framework based on geofence technology and geospatial analysis, this study breaks through the limitations of traditional manual on-site inspections and static supervision, realizes spatiotemporal matching and integrated governance of multi-source heterogeneous driver training data [22–23], and relies on the Shapely geospatial analysis library and DE-9IM model to achieve real-time monitoring of the compliance of training vehicle operations and automatic identification of violations. It forms a full-process closed-loop supervision mechanism covering pre-event early warning, in-event monitoring, and post-event traceability, providing an innovative technical solution to solve the problem of insufficient supervision efficiency in the driver training industry, and promoting the transformation of off-site supervision in the driver training industry towards intelligence and precision.

2 Research technical framework

To enhance the regulatory efficiency of the driver training industry, this study proposes an off-site supervision technical framework based on multi-source data fusion and intelligent analysis, and constructs a full-process system covering pre-event early warning, in-event monitoring, and post-event traceability. This technical framework breaks through the traditional government supervision model, and accurately defines violations and realizes real-time monitoring through a dynamically updated off-site supervision rule database. Relying on geospatial analysis and customized AI algorithms, the system can automatically screen hidden risk points, non-compliant enterprises, and key operating training vehicles in the multi-source dataset, and integrate the perception system with business data to improve identification accuracy.

In addition, the research technical framework introduces automated evidence collection and blockchain-based evidence solidification technology to ensure the authenticity and immutability of evidence. It pushes early warning information to relevant departments, forming a closed-loop supervision mechanism. This system significantly enhances supervision intelligence and response efficiency, demonstrating the innovative advantages of data-driven approaches and technology integration, as shown in Fig. 1.

3 Algorithm design for off-site supervision of the driver training industry

The proposed off-site supervision method for the driver training industry mainly relies on data processing and spatial analysis technologies. The core tools are Pandas (for data reading, processing, and analysis), Shapely (for geospatial analysis and determining whether a point is within the geofence), and Matplotlib (for data visualization). The specific processing procedures and discrimination processes are shown in Fig. 2.

3.1 Access and fusion of multi-source driver training data

To optimize data processing for off-site supervision in driver training and address the issues of fusion and governance of multi-source heterogeneous data in the driving training industry, this study accesses the driving training information platform to obtain multi-dimensional data, including geofence information, coach vehicle trajectory data, operation timestamps, and training records. The Python Pandas library is employed for preprocessing to construct a unified data analysis infrastructure. In this process, spatiotemporal constraints are applied to the data based on the defined training time periods and geofence ranges. Outliers in the time column are detected, and missing values in each column are handled. Subsequently, subject numbers are extracted, and data are grouped and sorted by subject and coach vehicle license plate, thereby achieving effective aggregation and fusion of multi-source

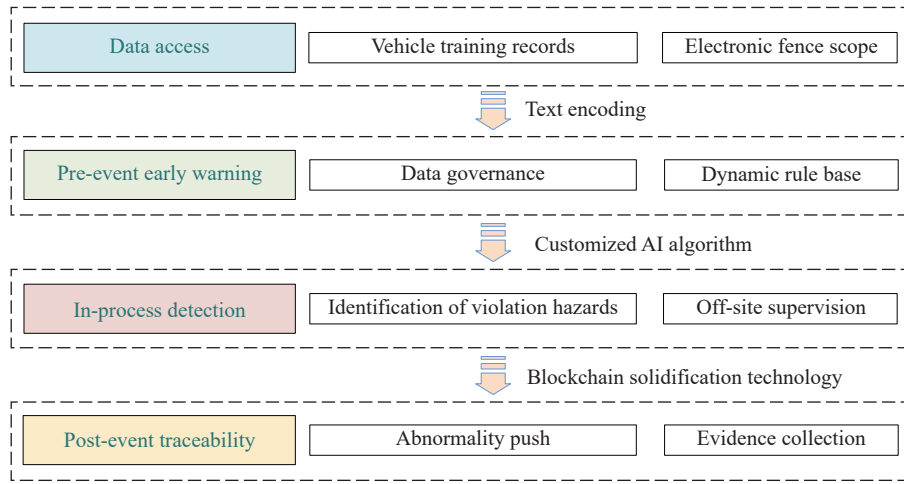


Fig. 1 Technical framework of off-site supervision in the driver training industry.

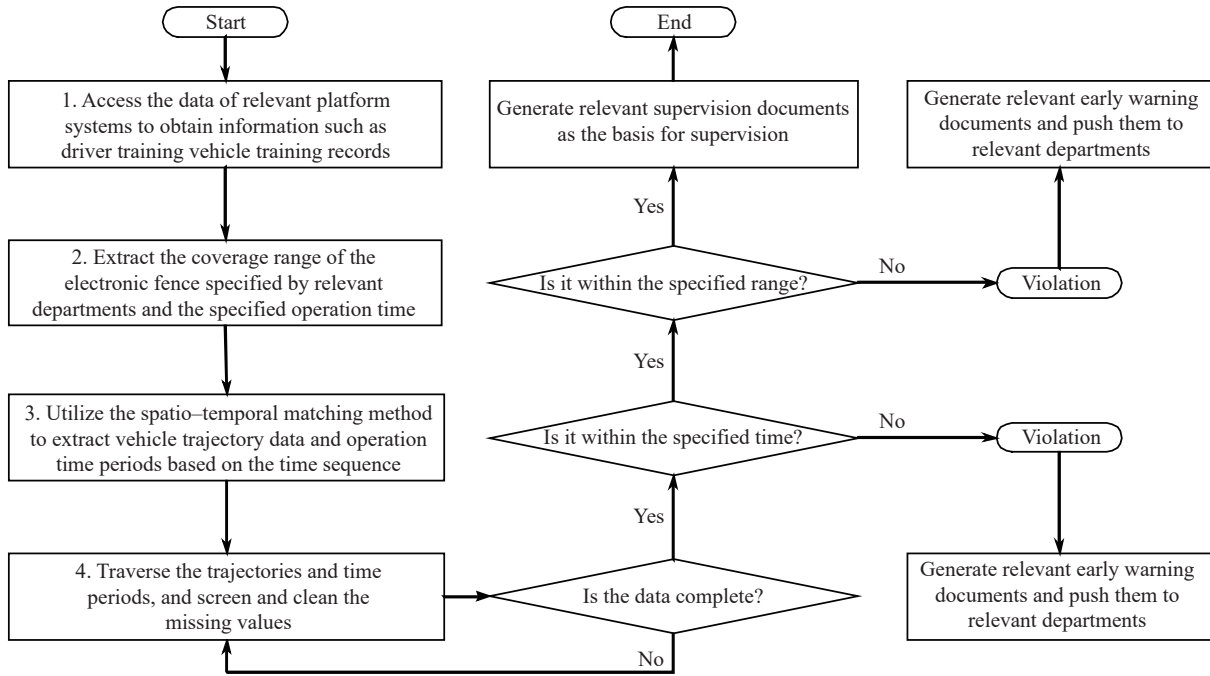


Fig. 2 Technical process of off-site supervision in the driver training industry.

data and laying a solid foundation for subsequent supervision and analysis.

3.2 Automatic identification of violation behaviors based on geospatial analysis

To address the long-standing challenges in the driver training industry, such as non-compliant operation of coach vehicles, irregular operating hours, and the inefficiency and lack of real-time performance of traditional supervision methods, this study proposes an innovative off-site supervision approach based on geospatial analysis technology. The aim is to realize automated and precise monitoring of coach vehicle operation behaviors and compliance judgment. By deeply mining multi-source industry data, this method breaks through the limitations of the traditional static and manual-dependent supervision mode, focusing on solving the scientific problems of insufficient dynamic management and poor coordination between in-event and post-event supervision.

Specifically, first, an geofence is constructed based on licensing information to accurately demarcate the compliant operation area for coach vehicles. By integrating real-time trajectory data, an optimized spatial matching algorithm is adopted to efficiently com-

pare the actual operating range of coach vehicles, thereby automatically identifying non-compliant behaviors that exceed the licensed area. Second, regarding the compliance of operating hours, timestamps in trajectory data are utilized, combined with advanced spatiotemporal analysis technology, to accurately determine whether the operation periods of coach vehicles conform to regulations through a spatiotemporal matching algorithm. In addition, the system integrates an intelligent anomaly detection mechanism to real-time mark operation behaviors that deviate from the compliant range or time, and generates data-driven decision support information, providing an efficient supervision basis for industry management departments.

3.2.1 Time compliance supervision method

(1) Specified time frame: 4:00–21:00 daily.

(2) Judgment logic: After sorting the trajectory data of each vehicle by time, check whether the time field ($x.time()$) of all records meets the following conditions:

$$start_time \leq x.time() \leq end_time$$

Return a boolean value (where True indicates full-period compliance).

3.2.2 Spatial compliance supervision method

Fence matching: Based on the training subject (Subject 2/3) of the vehicle, match the corresponding geofence.

Position Judgment: Construct GPS points via shapely.geometry.Point, and invoke Polygon.Contains(Point) to determine whether they lie within the fence.

Calculation of out-of-fence distance: If the vehicle is outside the fence, the Haversine formula is employed to calculate the straight-line distance from the current point to the nearest point on the fence boundary (in meters), with the formula as follows:

$$\begin{cases} a = \sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right) \\ c = 2 \cdot \arcsin(\sqrt{a}) \\ d = R \cdot c \end{cases}$$

where, ϕ_1 , λ_1 and ϕ_2 , λ_2 are the latitude and longitude of the two points (in radians); $\Delta\phi$ is the difference in latitude; $\Delta\lambda$ is the difference in longitude; R is the Earth's radius; d is the distance between the two points.

Determination of optimal threshold for coach vehicles exceeding fences based on SVM [24]:

First, data containing features such as maximum out-of-fence duration and maximum out-of-fence distance is prepared. After splitting the data into training and testing sets, stratified K-fold cross-validation is adopted to perform a grid search on the parameter grid. Finally, the optimal parameters are determined as {'C': 0.1, 'gamma': 0.001, 'kernel': 'rbf'}, and the accuracy of the model on the test set reaches 1.0000 with these parameters. The parameter tuning heatmap is shown in Fig. 3.

Logically, when the time threshold is set to 1 min, it can more sensitively capture short-term out-of-fence behaviors (avoiding missed detection of "short-duration but should-be-recognized as out-of-fence" scenarios due to an excessively large threshold). As for the spatial threshold set to 30 m, this distance can not only cover the reasonable spatial range for "should-be-recognized as out-of-fence" (eliminating overly strict misjudgments within 10–20 m) but also avoid the problem of "failure to recognize should-be-out-of-fence cases" caused by an overly wide range of 40–100 m. The combination of these two thresholds achieves the highest matching

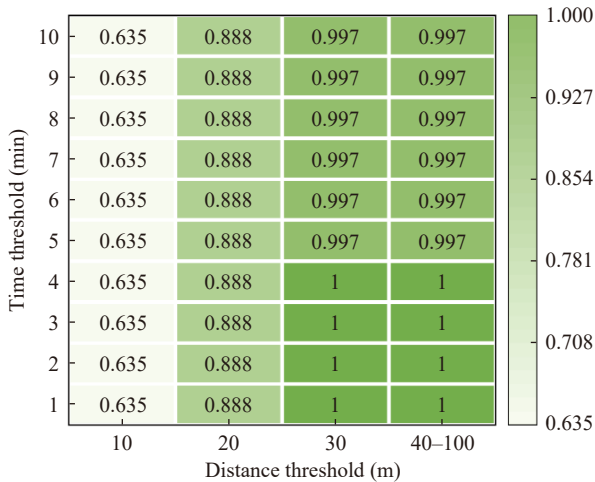


Fig. 3 The parameter tuning heatmap

degree with the actual situation in determining "whether a vehicle is out of the fence" among all tests, thus becoming the optimal threshold.

Therefore, the optimal out-of-fence thresholds are: the maximum out-of-fence duration is ≥ 1 min and the maximum out-of-fence distance is ≥ 30 m.

Deviation level definition:

(1) When the maximum out-of-fence duration is ≤ 0 min and the maximum out-of-fence distance is ≤ 0 m, there is no deviation, and the training behavior is considered spatially compliant.

(2) When the maximum out-of-fence duration is ≤ 1 min and the maximum out-of-fence distance is ≤ 30 m, it is classified as a minor deviation, but the training behavior is still considered spatially compliant.

(3) When the maximum out-of-fence duration is ≥ 1 min and the maximum out-of-fence distance is ≥ 30 m, it is classified as a severe deviation, and the training behavior is considered spatially non-compliant.

3.2.3 Compliance result determination

Based on the temporal and spatial verification results, the compliance of the training process is comprehensively determined. The determination rules are as follows:

Time compliance: is_in_time_period = True (all records fall within the time window of 4:00–21:00).

Spatial compliance: meets any of the following conditions:

(1) No out-of-fence events occur (out_of_fence_count = 0);

(2) Out-of-fence events occur, yet the maximum out-of-fence duration is ≤ 1 min and the maximum out-of-fence distance is ≤ 30 m.

Only when both the temporal and spatial dimensions meet the compliance requirements is the vehicle's training activity deemed compliant.

4 Case study of off-site supervision in the driver training industry

Based on the practical operation and business record data of a driving school in Beijing, this study conducts case analysis and verification research on model applicability for typical off-site supervision businesses in the driving training industry. The GPS positioning dataset of coach vehicles is shown in Table 1.

The case study process is shown in Fig. 4.

4.1 Layout of geofences

Based on the docking information from relevant authorities, the longitude and latitude information of geofences is obtained (Table 2). Combined with the Python platform, spatial processing is utilized to realize spatial mapping of the geofences and draw their boundaries.

The drawn geofence is shown in Fig. 5.

The visualization process of the GPS trajectory of the coach vehicle under its corresponding electronic fence is shown in Fig. 6.

4.2 Processing of coach vehicles' driving trajectories

The processing of coach vehicles' driving trajectories includes missing value processing, outlier processing and grouping-sorting processing.

For missing value processing, it is necessary to first detect missing conditions in each column: numeric columns (such as latitude

Table 1 GPS data of coach vehicles

Terminal identification	Latitude	Longitude	Time	Subject	Vehicle license plate
8 122 030 000 000 000	40.404 808	116.850 236	2024/12/1 7:52	1 212 000 000	*AEP99*
8 122 030 000 000 000	40.404 806	116.850 236	2024/12/1 7:53	1 212 000 000	*AEP99*
8 122 030 000 000 000	40.404 668	116.852 481	2024/12/1 7:54	1 212 000 000	*AEP99*
8 122 030 000 000 000	40.406 078	116.855 205	2024/12/1 7:55	1 212 000 000	*AEP99*
8 122 030 000 000 000	40.405 986	116.852 045	2024/12/1 7:56	1 212 000 000	*AEP99*

Note: Among them, the subject value is 1 212 000 000, where the 4th digit is 2, indicating subject 2.

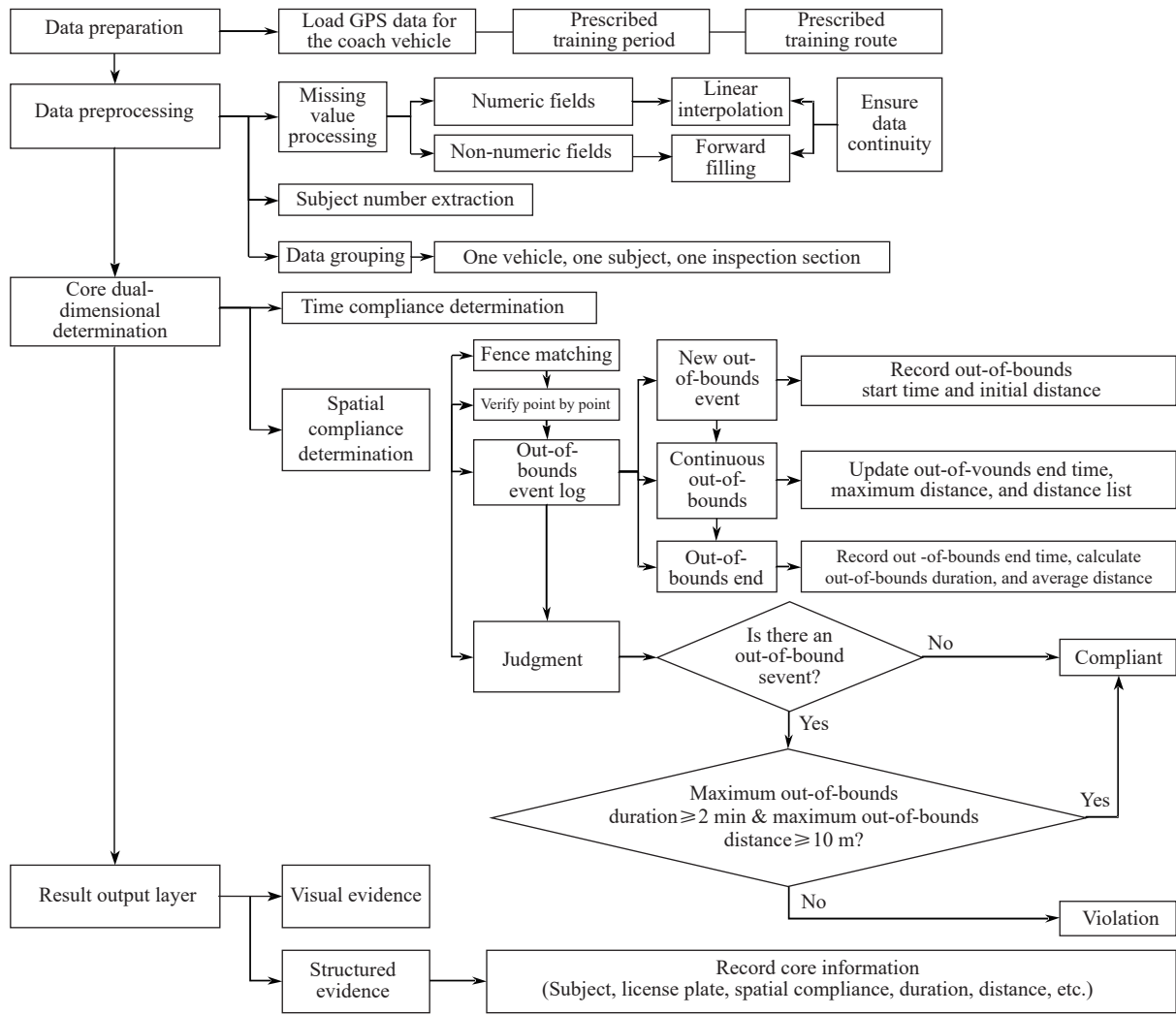


Fig. 4 Design process of off-site supervision algorithm for the driving training industry

Table 2 Geofence longitude and latitude information

Subject	3	2
	116.858 64,40.402 19;116.859 26,40.403 78;116.860 68,40.404 86; 116.860 31,40.405 67;116.853 01,40.408 13;116.846 04,40.406 79; 116.844 65,40.404 85;116.843 29,40.406 87;116.840 97,40.410 12; 116.837 57,40.413 44;116.835 27,40.415 82;116.832 31,40.419 64; 116.830 74,40.423 41;116.828 99,40.426 48;116.827 77,40.428 99; 116.827 51,40.432 38;116.827 26,40.434 49;116.827 01,40.437 77; 116.826 03,40.437 86;116.825 96,40.435 60;116.825 83,40.433 55; 116.825 84,40.432 06;116.825 96,40.430 94;116.826 06,40.429 81; 116.826 19,40.428 77;116.826 55,40.427 84;116.827 03,40.426 85; 116.827 62,40.425 86;116.828 20,40.424 57;116.828 62,40.423 83; 116.829 31,40.422 26;116.830 33,40.420 35;116.831 11,40.419 04; 116.832 08,40.417 22;116.832 93,40.416 18;116.834 96,40.414 11; 116.837 17,40.411 47;116.839 57,40.409 46;116.840 93,40.406 72; 116.841 67,40.404 57;116.841 92,40.402 26;116.845 76,40.401 98; 116.848 88,40.401 89;116.851 78,40.402 44;116.852 98,40.403 16; 116.856 08,40.402 78	116.85507,40.40326;116.85737,40.40279; 116.85815,40.40212;116.85901,40.40265; 116.85916,40.40371;116.86032,40.40418; 116.86055,40.40555;116.85806,40.40572; 116.85499,40.40736;116.85290,40.40791; 116.84966,40.40758;116.84643,40.40710; 116.84551,40.40645;116.84671,40.40539; 116.84810,40.40620;116.85068,40.40637; 116.85055,40.40566;116.84924,40.40530; 116.85004,40.40362;116.85120,40.40294; 116.85304,40.40335

and longitude) are filled with linear interpolation, while non-numeric columns (such as vehicle license plates) are filled using forward filling.

For outlier processing, first remove these outliers, and then perform imputation in accordance with missing value imputation methods.

For grouping-sorting processing, the subject number is extracted from the “Subject” field, and data are grouped by “subject number + vehicle license plate”. Each group of data is sorted in ascending order by the “Time” column to ensure the temporal continuity of the trajectories.

The processing results are shown in Table 3.

4.3 Analysis of automatic discrimination results

The automatic discrimination results are shown in Table 4. When the maximum out-of-fence duration is ≤ 1 min and the maximum out-of-fence distance is ≤ 30 m, only a small number of vehicles exhibit non-compliant training activities.

4.4 Result evaluation

To evaluate the results of the off-site supervision method for the driver training industry, data on the operation records of coach vehicles from a driving school was accessed. The automatic identification algorithm for coach vehicle non-compliance was adopted

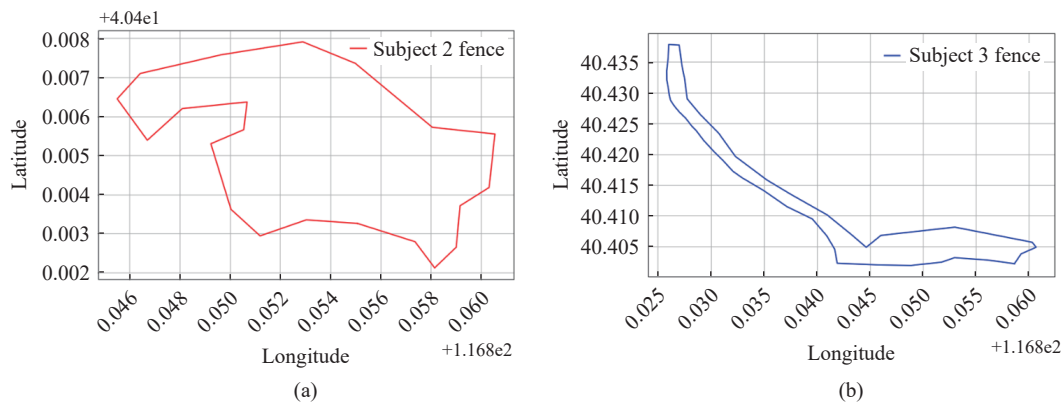


Fig. 5 Layout range of geofences. (a) Subject 2 electronic fence; (b) Subject 3 electronic fence.

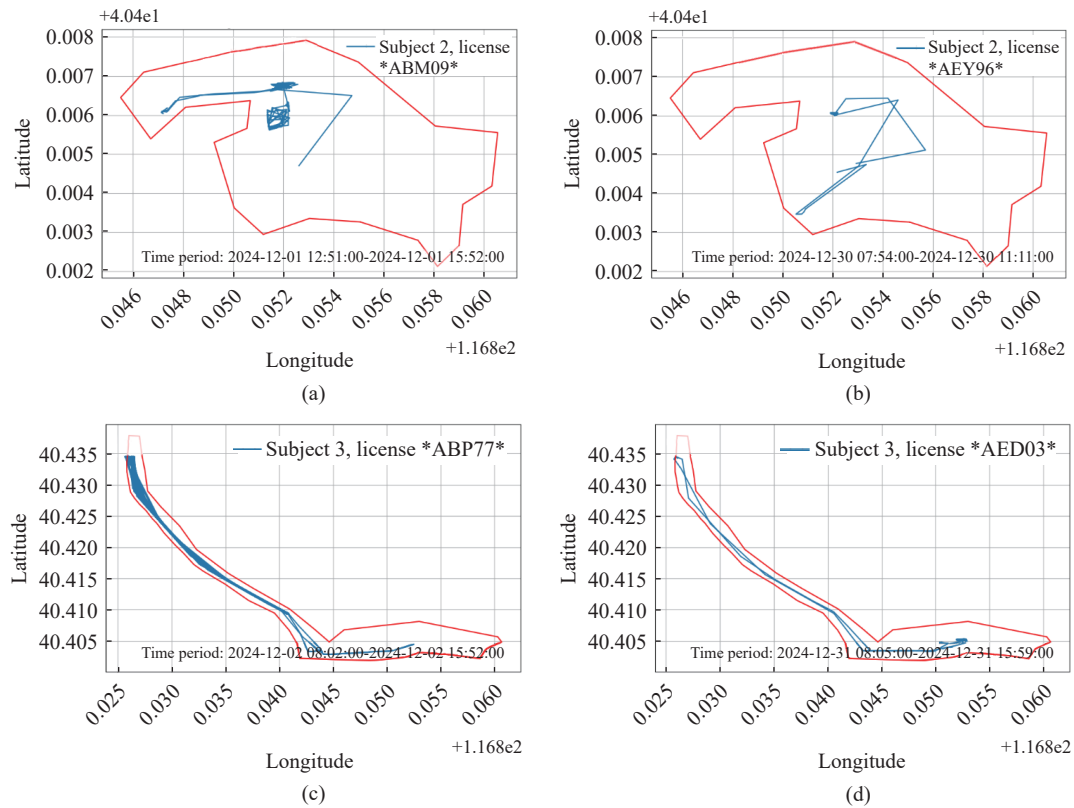


Fig. 6 Trajectory maps of some coach vehicles. (a) Subject 2, license*ABM09* path; (b) Subject 2, license*AEY96* path; (c) Subject 3, license*ABP77* path; (d) Subject 3, license*AED03* path.

Table 3 Results of data preprocessing

Terminal identification	Latitude	Longitude	Time	Vehicle license plate	Subject
8 122 030 000 000 000	40.404 70	116.852 6	2024-12-01 12:51:00	*ABM09*	2
8 122 030 000 000 000	40.406 50	116.854 7	2024-12-01 12:52:00	*ABM09*	2
8 122 030 000 000 000	40.406 66	116.851 6	2024-12-01 12:53:00	*ABM09*	2
8 122 030 000 000 000	40.406 65	116.851 6	2024-12-01 12:54:00	*ABM09*	2
8 122 030 000 000 000	40.406 65	116.851 6	2024-12-01 12:55:00	*ABM09*	2
8 122 030 000 000 000	40.406 66	116.851 6	2024-12-01 12:56:00	*ABM09*	2
8 122 030 000 000 000	40.406 67	116.851 6	2024-12-01 12:57:00	*ABM09*	2
8 122 030 000 000 000	40.406 67	116.851 6	2024-12-01 12:58:00	*ABM09*	2

to identify and manage whether coach vehicles operate within the specified routes and time. Meanwhile, after data fusion, the traditional manual recording method was also used for non-compliance identification on this part of the data, and a comparative analysis of the two sets of identification results was conducted. The identification results are shown in Table 5.

In the above data tables, the algorithm-identified non-compliance refers to the results of automatic identification of coach

vehicles' non-compliant behaviors based on the off-site supervision method; the post-identification manual verification is a recheck of the identification results from the off-site supervision method, aiming to verify the identification accuracy.

Next, quantitative analysis is conducted using the core evaluation indicators in the supervision scenario (Accuracy, Precision, Recall, F1-Score):

First, extract key data from Table 5, define the P_T as true posit-

Table 4 Discrimination results

Date	Subject	License plate	Within training time	Within geofence	Out-of-fence count	Max out duration (min)	Max out distance (m)
2024-12-01	2	*ABM09*	TRUE	TRUE	0	0	0
2024-12-01	2	*AEP99*	TRUE	TRUE	0	0	0
2024-12-01	3	*ABM09*	TRUE	TRUE	0	0	0
2024-12-01	3	*ADG99*	TRUE	TRUE	0	0	0
2024-12-02	2	*ABL69*	TRUE	TRUE	0	0	0
2024-12-02	2	*ADG99*	TRUE	TRUE	0	0	0
2024-12-02	2	*ADH66*	TRUE	TRUE	0	0	0
2024-12-02	3	*ABP77*	TRUE	TRUE	10	0	21.573
2024-12-02	3	*ADG99*	TRUE	FALSE	5	5	21.095

Table 5 Comparative analysis of identification results

Subject	Off-site supervision items	Total samples	Algorithm identification	Manual verification
2	Exceeding the training time period	149	0	0
	Exceeding the geofence	149	1	1
3	Exceeding the training time period	226	0	0
	Exceeding the geofence	226	5	4

ive, N_T as true negative, P_F as false positive, N_F as false negative (see Table 7). The indicator formulas and their meanings are shown in for each supervision item (see Table 6), then organize the data (see Table 8).

Table 6 Four elements of the confusion matrix

Terms	Definition (with “Non-Compliance” as Positive)
P_T	The algorithm identifies it as “Non-Compliance”, and the manual verification also confirms it as “Non-Compliance”
N_T	The algorithm identifies it as “Compliance”, and the manual verification also confirms it as “Compliance”
P_F	The algorithm identifies it as “Non-Compliance”, but the manual verification confirms it as “Compliance” (Misjudgment)
N_F	The algorithm identifies it as “Compliance”, but the manual verification confirms it as “Non-Compliance” (Missed Judgment)

Table 7 Data collation

Subject	Off-site supervision items	P_T	N_T	P_F	N_F
2	Exceeding the training time period	0	149	0	0
2	Exceeding the geofence	1	148	0	0
3	Exceeding the training time period	0	226	0	0
3	Exceeding the geofence	4	221	1	0

Table 8 Formulas and meanings of indicators

Indicators	Formula	Meaning in the supervision scenario
$R_{Accuracy}$	$(P_T + N_T) / (P_T + N_T + P_F + N_F)$	Reflects comprehensive correctness
$R_{Precision}$	$P_T / (P_T + P_F)$	Avoids misjudgment
R_{Recall}	$P_T / (P_T + N_F)$	Avoids missed judgment
F_1	$2 \times (R_{Precision} \times R_{Recall}) / (R_{Precision} + R_{Recall})$	Balances misjudgment and missed judgment

Calculations are performed for each supervision item one by one, with a focus on the “Exceeding the geofence” item that has “non-compliant samples”. For “Exceeding the training time period”, there is no actual non-compliance, so Precision/Recall are meaningless. The calculation results are shown in Table 9.

The P_T , N_T , P_F , and N_F of the four supervision items are aggregated (total samples $149 + 149 + 226 + 226 = 750$). The aggregated confusion matrix is as follows: $P_T = 5$, $N_T = 744$, $P_F = 1$, $N_F = 0$. The calculation results are shown in Table 10.

From the perspective of indicator results, the performance of this off-site supervision algorithm fully meets the supervision needs of the driver training industry. Its core advantages are reflected in the following three aspects:

(1) No missed judgments (R_{Recall} as 100%): All actual non-compliant behaviors (a total of 5 cases) were identified by the algorithm, with no false negatives ($N_F = 0$). The 100% Recall rate ensures that “no non-compliant behaviors are missed”, which aligns with the core objective of supervision.

(2) Low misjudgments ($R_{Precision}$ as 83.33%): There is only 1 case of False Positive (for the Subject 3 item of exceeding the geofence), meaning the algorithm misidentified 1 case of compliant training as non-compliant. Although False Positives incur a small amount of manual verification costs, this misjudgment rate is acceptable compared to the safety risks of missed judgments. Furthermore, such errors can be quickly corrected through subsequent secondary manual verification.

(3) High comprehensive accuracy (R_{OA} as 99.87%): Nearly 99.9% of samples were correctly identified. In particular, all samples for the exceeding the training time period item were accurately identified as compliant, and there were zero errors for the Subject 2 exceeding the geofence item. This indicates that the algorithm has high stability across different supervision scenarios and does not rely on extensive manual intervention.

In conclusion, the automatic identification of coach vehicles’

Table 10 Overall indicator calculation results

Indicators	Calculation process	Results (%)
R_{OA}	$(5+744)/750$	99.87
R_{OP}	$5/(5+1)$	83.33
R_{OR}	$5/(5+0)$	100
F_{IO}	$2 \times (0.8333 \times 1) / (0.8333 + 1)$	90.91

Note: OA is overall accuracy; OP is overall precision; OR is overall recall; O is overall.

Table 9 Indicator calculations for single supervision items

Subject	Off-Site supervision items	$R_{Accuracy}$	$R_{Precision}$	R_{Recall}	F_1
2	Exceeding the training time period	100%	—	—	—
2	Exceeding the geofence	100%	100%	100%	100%
3	Exceeding the training time period	100%	—	—	—
3	Exceeding the geofence	99.56%	80%	100%	88.89%

non-compliant behaviors using the off-site supervision method can well meet the needs of relevant authorities, improve the quality and efficiency of non-compliance identification, and thereby enhance the supervision effectiveness of the driver training industry.

4.5 Analysis of error sources

(1) The GPS equipment of coach vehicles, affected by environmental obstructions (such as high-rise buildings) and electromagnetic interference (such as signal conflicts from surrounding base stations), may produce a positioning drift of 5–15 m. That is, the actual vehicle is still within the geographical fence, but the positioning data shows it is beyond the fence boundary. Moreover, due to the short duration of the drift, it may trigger a “slight deviation” judgment.

(2) The geographical fence is constructed based on longitude and latitude coordinates, but in actual training scenarios, the fence boundary may correspond to a blurred area in physical space. For example, the “road edge” of the subject 3 training route has no clear physical markers, resulting in differences between algorithmic judgments and manual observations when the vehicle is close to the boundary.

(3) When the trajectory data of coach vehicles is uploaded to the supervision platform via 4G/5G networks, network fluctuations (such as weak signals in suburban areas) may cause a data transmission delay of 30 s to 2 min. That is, the vehicle has actually returned to the fence, but the delayed data shows it is still outside, leading to an overlong statistics of “duration outside the fence”.

Improvement plans:

(1) Integrate GPS positioning with Beidou positioning and inertial navigation (IMU) to build a “multi-source positioning correc-

tion model”. When GPS drifts, verify the position through Beidou positioning (which has stronger anti-occlusion capability with a drift of ≤ 5 m). If the deviation between the two exceeds 5 m, enable inertial navigation (calculating position based on vehicle acceleration and angular velocity without external interference) to supplement positioning and correct drift data.

(2) Introduce a “field calibration mechanism”. Update the geographical fence coordinates through drone aerial photography and manual field measurement every quarter to correct the deviation between physical boundaries and coordinate annotations.

(3) Add a “local edge computing module” to the coach vehicle terminal to perform real-time preprocessing on trajectory data first. If network delay is detected (such as data upload timeout of 30 seconds), temporarily store the data locally and predict the subsequent position based on the vehicle’s speed and direction. After the network is restored, compare the “predicted position” with the “actual uploaded position” to correct the statistical deviation of “duration outside the fence” caused by delay.

4.6 Visual management of off-site supervision in the driver training industry

The off-site supervision method for the driver training industry has realized the off-site supervision visualization management of whether training vehicles operate in accordance with the specified time and routes. The specific applications are as follows:

(1) Based on the accessed data, the proposed off-site supervision method has realized real-time monitoring of the operation status of training vehicles. As shown in Fig. 7, the automatic identification and supervision model can focus on real-time supervision of the real-time location and operating time of training vehicles.

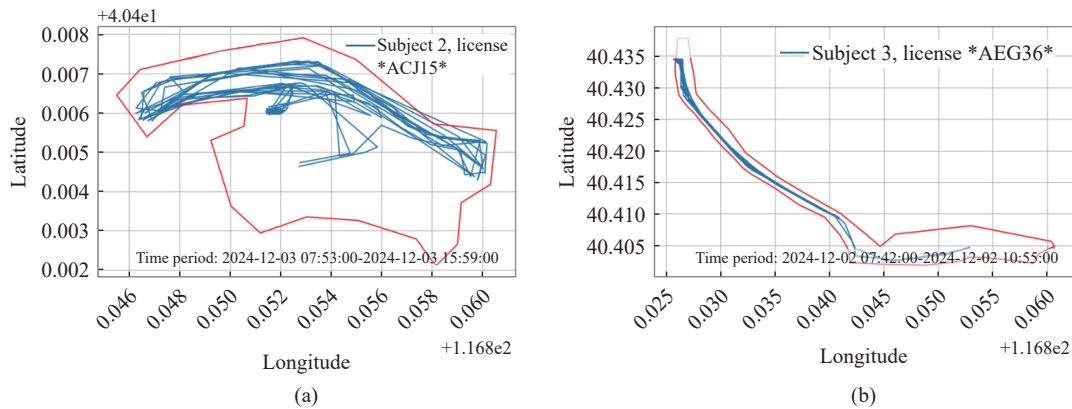


Fig. 7 Results of off-site supervision. (a) Subject 2, license*ACJ15* path; (b) Subject 3, license*AEG36* path.

(2) Using the aforementioned off-site supervision model, real-time identification of training vehicle violations is realized. As shown in Fig. 8, when a training vehicle violates regulations, real-

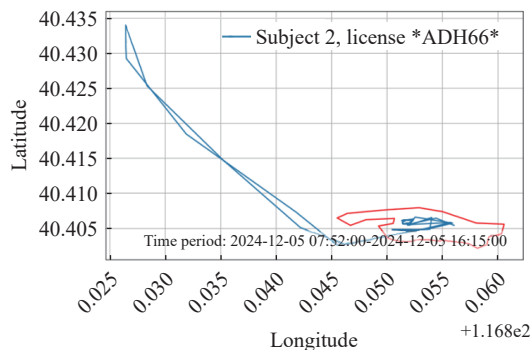


Fig. 8 Discrimination of violation cases (Subject 2, license *ADH66* path).

time records will be generated, allowing access to information about the violating vehicle, as well as details of the violation incidents and behaviors.

(3) Based on geospatial analysis of multi-source data from the driver training industry, this study automatically determines the compliance of training vehicles’ actual operating range and operating time in accordance with relevant licensing information. The proposed off-site supervision method for the driver training industry can real-time identify illegal operating behaviors, generate early warning information and push it to regulatory authorities, providing data support for “in-event + post-event” supervision. Table 11 shows examples of early warnings for some illegal operating behaviors.

4.7 Push of early warning information

4.7.1 Trigger rules for graded early warnings

(1) No deviation (maximum out-of-fence duration ≤ 0 min + maximum out-of-fence distance ≤ 0 m): No early warning is

Table 11 Early warning examples of illegal operation behaviors

Date	Subject	Vehicle license plate	Whether within the training time period	Whether within the geofence	Violation information	Pushed to department	Suggested measures
12/05	2	*ADH66*	TRUE	FALSE	Significantly deviated from the specified range	Driver training department	Conduct an immediate inspection
12/13	3	*ABL69*	TRUE	FALSE	Slight anomaly, requires attention	Driver training department	Record and issue a warning

triggered.

(2) Minor deviation (maximum out-of-fence duration ≤ 1 min + maximum out-of-fence distance ≤ 30 m): Triggers a “Level 1 Warning (Prompt Warning)”.

(3) Severe deviation (maximum out-of-fence duration ≥ 1 min + maximum out-of-fence distance ≥ 30 m): Triggers a “Level 2 Warning (Emergency Warning)”. Such deviations are classified as spatial violations, and the system adopts a “real-time triggering + continuous tracking” mechanism. Once a coach vehicle is detected to be out of the fence for more than 1 min or at a distance exceeding 30 m, a Level 2 Warning is immediately triggered. Meanwhile, the vehicle’s position is continuously tracked; if it fails to return to the fence within 10 min, the warning is upgraded to a “Level 3 Warning (Supervision-driven Warning)”, mandating regulatory personnel to intervene and verify.

4.7.2 Mechanism for push of early warning information and synchronization of evidence

(1) Level 1 warning: Pushed only to the driving school management terminal. The content includes “vehicle license plate, deviation time period, deviation location (latitude and longitude + map annotation), and cumulative number of deviations”. The driving school shall independently urge the coach to rectify the issue, and regulatory authorities may access the early warning records at any time.

(2) Level 2/Level 3 warnings: Synchronously pushed to both the driving school management terminal and local driving training regulatory authorities. In addition to basic information, the content shall include “trajectory screenshots (marking the start/end points of out-of-fence events)” and “distance calculation process (parameters and results of the Haversine formula)”, ensuring that regulatory authorities can conduct rapid verification without the need for secondary evidence collection.

5 Research conclusions and prospects

This study proposes an AI algorithm-based off-site supervision method for the driver training industry, designed to achieve off-site supervision and automatic identification of whether coach vehicles operate in compliance with regulations.

The method utilizes geofence technology and geospatial analysis methods to complete the access and fusion of multi-source heterogeneous driver training data. It enables automatic identification and off-site supervision of whether coach vehicles operate in accordance with the routes and time specified by relevant authorities. Taking a driving school in Beijing as an example, the effectiveness of the proposed method was verified.

Specific conclusions indicate that the comprehensive supervision framework not only realizes the integrated governance and visual representation of multi-source heterogeneous driver training data but also accurately and automatically determines the operational compliance of coach vehicles, with an overall accuracy rate of 99.87%. This further verifies the effectiveness and reliability of the proposed method. The research results support the integrated comprehensive management and off-site supervision of the driver training industry: by generating electronic supervision records and pushing non-compliant behaviors to relevant authorities, it provides a basis for “in-event + post-event” supervision.

While the proposed off-site supervision method for the driver training industry can effectively identify the non-compliant behaviors of coach vehicles, the current research still has limitations. In particular, when there are extensive overlaps and gaps between

coach vehicle trajectories and geofence boundaries, a decrease in model accuracy is observed. More detailed and in-depth follow-up research is required in this area in the future. Secondly, due to certain special reasons, only one month’s trajectory data could be obtained from the driving school. Therefore, the regulatory model is insufficient in persuasiveness regarding both its universality and applicability. However, efforts will be made to enhance the universality and applicability of the model in the future.

Acknowledgements

We extend our appreciation to the colleagues and institutions who provided the original data that formed the basis of this research. We are also deeply thankful to the journal editors for their professional valuable editorial suggestions, which greatly improved the quality of this manuscript.

Funding

This research was sponsored by the Beijing Municipal Commission of Transport Science and Technology Project Research and Application of Key Technology and Intelligent Equipment Optimization Algorithm for Off-site Supervision in Transportation Industry (Grant No. BJJTW-2024-DSJ-16).

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author contribution statement

Zhang Xin: conceptualization, data curation, funding acquisition, methodology, software, writing original draft, review & editing. Xu Shuo: data curation, methodology, investigation. Wu Keqi: data curation, investigation, methodology, software, writing original draft. Xiao Hui: formal analysis, project administration, supervision, writing review & editing. Shen Huapeng: investigation, validation, writing original draft. Wang Houyong: investigation, validation, editing. Zhang Yuanmeng: formal analysis, investigation. Zhang Xiaoliang: formal analysis, investigation, resources.

Data availability statement

Certain proprietary datasets used in this study are subject to non-disclosure agreements with third-party collaborators, which restrict the sharing of such data with external parties without explicit written consent.

Use of AI statement

During the preparation of this research, we used ChatGPT to improve grammar and readability. After using this tool, we reviewed and edited the content as needed and take full responsibility for content of the publication.

References

- [1] Tan Y. Accelerating transformation and upgrading to promote the healthy development of the driver training industry. *Road Traffic Management*, 2021(6): 88–89.
- [2] Zou XL. On the Healthy Development of Scientific and Technological Innovation in Driving Training Industry. *Auto Times*, 2022(3): 40–41.

- [3] Heydari M, Heravi G, Raesinafchi R, et al. A dynamic model to assess the role of site supervision systems in the safety performance of construction projects. *Journal of Construction Engineering and Management*, 2024, 150(3): 04024001.
- [4] Wang SC, Mack EA, Kalani N, et al. Workforce development in the trucking industry: A comprehensive analysis of truck driver training entities. *Transport Economics and Management*, 2025, 3: 23–34.
- [5] Yuan HY. Construction planning and analysis of river water ecological informatization supervision platform. *Water Conservancy Science and Technology and Economy*, 2024, 30(4): 7–13. doi:10.3969/j. issn.1006-7175.2024.04.002.
- [6] He ZH, Shao RC, Xiang SJ. Vehicle trajectory generation based on generation adversarial network. *Journal of Highway and Transportation Research and Development (English Edition)*, 2024, 18(2): 82–88.
- [7] Yang JB, Lu GY, Li L, et al. Microseismic electronic fencing for monitoring of transboundary mining in mines. *Applied Sciences*, 2024, 14(23): 11043.
- [8] Liu ZX, Zhang HB. On the application of ais in maritime intelligent IT management and the existing problems. *China Maritime Safety*, 2019(8): 45–48.
- [9] Sun SY, Xu ZZ, Liu SX, et al. Design and implementation of national marine dumping supervision and management system. *Marine Environmental Science*, 2023, 42(1): 160–164.
- [10] Zhang X, Xu S, Wu KQ, et al. Research on the Informatization Supervision Model of Beijing Bus Transit Industry. *Journal of Transportation Engineering*, 2025, 25(1): 62–66, 72.
- [11] Liu CX. Public transport industry supervision platform based on big data collection and analysis. Dalian: Dalian University of Technology, 2018.
- [12] Zhang X, Xu S, Wu KQ. Research on the off-site supervision mode of Beijing motor vehicle maintenance industry. *Auto & Safety*, 2024 (4): 70–75.
- [13] Li YK. Application of information technology in the governance of over-limit and over-load transportation. *China Logistics & Purchasing*, 2025(10): 93–94.
- [14] Ma HS. The procedure standardization construction of off-spot law enforcement of traffic police. People's Public Security University of China, 2023.
- [15] Zhao HY. Research on off-site law enforcement procedures for traffic administrative penalties. Inner Mongolia University, 2023.
- [16] Chen J. Problems and standardization path of transportation off-site law enforcement in the era of artificial intelligence. *Qiche Huakan*, 2025(3): 29–31.
- [17] Sun HT, Liu RX. Procedural issues and optimization of traffic off-site law enforcement. *Journal of Heilongjiang Administrative Cadre College of Politics and Law*, 2025 (2): 21–26.
- [18] Huang XH, Wang YJ. Institutional innovation in platform economy regulation: An extended analysis of the embeddedness of responsive regulation theory. *Information Technology and Management Application*, 2023, 2(4): 55–66.
- [19] Tao JQ, Zhang XC, Liu JG, et al. "Mucang Technology" practice in driver training services. *People's Tribune*, 2022 (8): 106–108.
- [20] Liang SJ, Xie HT, Guo LY, et al. Intelligent management of the driver training industry based on the "cloud service" platform. *East China Science and Technology*, 2022(1): 62–64.
- [21] Li ZH. Blind spots in multi-department supervision in driving training industry and countermeasures. *Automobile Maintenance and Repair*, 2025(7): 14–16.
- [22] Yu JY, Hu Y, Li J, et al. Trajectory data based comprehensive quantitative method for light-duty vehicle dynamic lane-changing risk on urban expressway. *Journal of Highway and Transportation Research and Development*, 2025, 42(2): 13–22.
- [23] Wang JS, Xu H, Miao ZY. Study and application of multi fine-grained tunnel traffic flow prediction model based on spatio-temporal relation. *Journal of Highway and Transportation Research and Development*, 2024, 41(11): 86–93.
- [24] Sun RR, Zhang JX, Zhu GY. A real-time recognition model of dangerous traffic flow state based on SVM. *Journal of Highway and Transportation Research and Development*, 2021, 38(10): 120–128.