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Driving Risk Identification of Truck Drivers Based on China's Highway Toll Data

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Abstract: Dangerous or illegal driving may disrupt the traffic safety management of public security organs, damage road infrastructure, lead to traffic accidents, or result in economic losses. This paper proposes a framework based on China's highway toll data to identify dangerous or illegal driving risks, such as unfamiliarity with road conditions, overload, driving over the speed limit, fatigued driving, fake license plates, and other risks. The unfamiliarity with road conditions is identified with the frequency of driving routes. When the total weight of a vehicle and its cargo is greater than the upper limit of the total weight of the vehicle and its cargo, the vehicle can be judged as overloaded. When the actual travel time is less than the minimum travel time, it can be inferred that the vehicle has a risk of fatigued driving, driving over the speed limit, a fake license plate, or other risks. Two accidents are used to demonstrate the process of the proposed framework for identifying driving risks based on China's highway toll data. Additional analysis proves that the proposed framework can be used to identify dangerous or illegal driving risks, and it provides a scientific basis for the traffic safety management of public security organs, reducing infrastructure damage, and avoiding the loss of national taxes and fees.

Keywords: driving risk; highway toll data; overload; illegal driving

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1. Introduction

Individual participants are important components of the transportation system. Dangerous or illegal driving risks of individual participants, such as unfamiliarity with the road conditions [1], overload [2], driving over the speed limit [3], fatigued driving [4], and fake license plates, often disrupt the traffic safety management of public security organs, damage road infrastructure, lead to traffic accidents, and result in economic losses. For example, overload may lead to tire bursts, vehicle imbalance, brake failure, steering loss of control, road damage, bridge fracture, operational errors, etc. Fake license plates may harm the interests of actual car owners, disrupt the public security organs' control of traffic safety, and cause a significant loss of national taxes and fees. Identifying driving risks in the transportation system is an effective means to curb dangerous and illegal driving and promote the sustainable development of the transportation system.

In previous research, the conventional travel characteristics studied have included travel distance [5], travel time [6], departure time [7], arrival time [8], travel duration [5], trip frequency [9], trip length [8], route choice [10], trip purpose [9], mode choice [11], station choice [6], travel pattern [12], etc. For example, the concept of stickiness was introduced to describe a tendency to stick to one route [10]. The trip frequency, departure time, arrival time, and trip length in the transportation hub were analyzed for security monitoring [8]. Trip characteristics were studied, including access and egress mode, trip purpose, station choice, and travel time [6]. The complexity of the relationship between the built environment and travel behavior was explored by drawing on causal insights from social psychology theories [13]. Travel characteristics were explored in terms of mode choice, trip distance, trip frequency, the use of alternative transport, ridesharing, and mobility tool ownership [11].

Trucks exceeding the legal axle and gross vehicle weight limit may cause serious damage to infrastructure [14,15] and increase the risk of traffic crashes [2,16]. For example, the high traffic volume of overloaded trucks led to the sudden failure of road pavement structures in Niger State, Nigeria, in 2020 [17]. Notably, 62% of trucks in truck collisions were overloaded in the United Arab Emirates [15]. Five regression trees were developed to analyze the truck and axle overload and predict overweight trucks from historical weigh-in-motion data involving a Brazilian highway [16]. The results revealed that the most important variable in classifying and predicting overload was vehicle classification, and the most significant variable regarding axle overload was the time of the day, i.e., most of the overloaded trucks traveled late at night or in the early morning. The impact of overloaded heavy trucks in Abu Dhabi was assessed by conducting a trend analysis using weigh-in-motion data [15]. The results revealed that 61% of trucks passing through the weigh-in-motion stations were overloaded, and winter months reported the highest violations.

Fatigued driving is a significant cause of traffic accidents [4,18,19]. Thus, detecting fatigued driving is an effective approach to preventing traffic accidents [20,21]. In previous studies, the fatigued driving state in a low-voltage and hypoxia plateau environment was studied with drivers' real-time electroencephalogram signals [20]. A functional brain network was constructed to recognize the fatigued driving state, and the neural mechanism of fatigued driving was analyzed [22]. A complete embedded system was presented to detect fatigued driving using deep learning, computer vision, and heart rate monitoring [19]. A fatigued driving recognition framework was proposed, which could denoise the electroencephalogram signals based on a deep convolutional neural network and the dynamically constructed functional brain network [23]. Ensemble empirical mode decomposition and power spectral density were combined to detect fatigued driving using electroencephalography [24]. The deep learning-based fatigue detection method was investigated, and a multimodal signal fatigue detection method was proposed [25]. A fatigued driving detection algorithm was proposed based on an end-to-end temporal and graph convolution [21]. A communication-efficient federated learning method was proposed for fatigued driving supervision [26]. An association rule mining approach was applied to explore the risk factors that lead to the inattention of hazardous materials truck drivers [27].

Fake license plates can harm the interests of actual car owners, disrupt the control of public security organs over traffic safety, and cause significant losses in national taxes and fees [28]. Specifically, vehicles with fake license plates lack legal procedures and insurance, disrupting the control of public security organs over traffic safety and providing tools for criminal activities. Drivers of vehicles with fake license plates fail to pay various taxes and fees, such as vehicle purchase tax, road maintenance fees, etc., resulting in significant losses in national taxes and fees. Those with fake license plates can evade punishment for traffic violations and harm the legitimate rights and interests of actual car owners. After a traffic accident, the actual car owner who is voluntarily falsely licensed often cooperates with the dealer to request compensation from the insurance company, resulting in fraudulent insurance claims. In previous studies, deep learning was used to recognize license plates [29–31]. Deep neural networks were used to recognize fake license plates, including the vehicle manufacturers, models, and colors [32].

The data used in the previous studies mainly include survey data [9], smart card data [33], mobile phone data [5], GPS data [7], weigh-in-motion data [15], videos [26], electroencephalogram signals [23], etc. There is still a lack of research on driving risks based on highway toll data. Some researchers have studied fatigued driving based on electroencephalogram signals. However, electroencephalogram signals have not been fully popularized. Not all vehicles are equipped with electroencephalogram signal detection equipment. Thus, this paper proposes a framework for analyzing driving risks based on highway toll data, including unfamiliarity with road conditions, overload, driving over the speed limit, fatigued driving, and fake license plates. A flowchart of this research is shown in Figure 1.

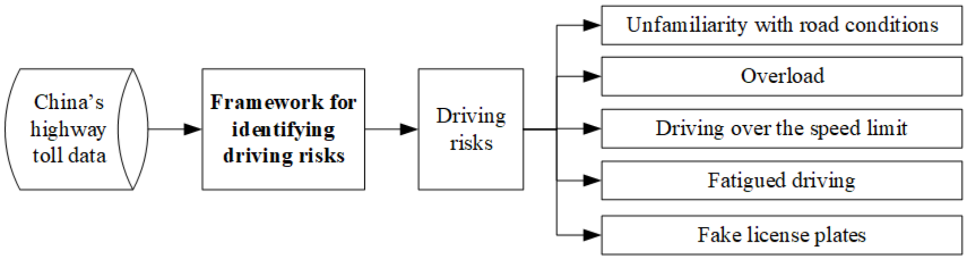

Figure 1. Research flowchart.

The remainder of this paper is organized as follows. Section 2 proposes the framework for analyzing driving risks based on highway toll data. A case study is presented in Section 3 to demonstrate the process of the proposed framework. Section 4 gives an additional application to verify the effectiveness of the proposed framework. Finally, the conclusions, limitations, and future research directions are discussed in Section 5.

2. Methods

2.1. Framework

The framework for identifying driving risks based on highway toll data is shown in Figure 2.

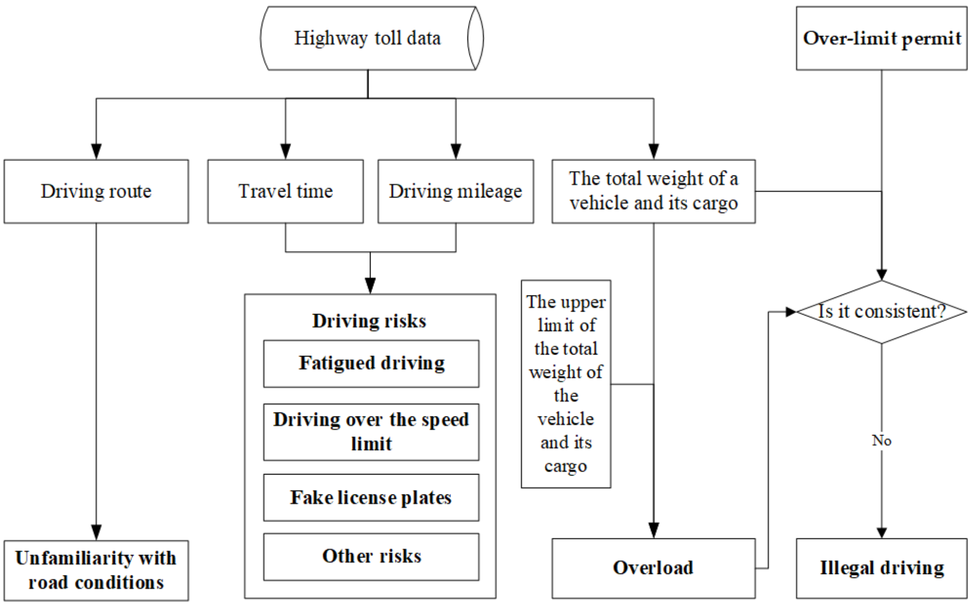

Figure 2. Framework for identifying driving risks based on highway toll data.

Highway toll data are obtained through toll stations and toll gantries. Vehicles enter the highway network at the entrance toll stations and leave the highway at the exit toll stations. To record the vehicles' driving trajectories from the entrance toll stations to the exit toll stations, more than twenty-nine thousand sets of toll gantries have been installed on highways for electronic toll collection (ETC) in China. The number of ETC users exceeds 290 million. The daily fee data exceed 1 billion. The daily traffic volume at the exit toll station exceeds 32 million vehicles. The driving route, travel time, driving mileage, and the total weight of a vehicle and its cargo can be extracted from highway toll data.

A framework for identifying driving risks based on highway toll data is proposed to detect unfamiliarity with road conditions, overload, driving over the speed limit, fatigued driving, and fake license plates. (1) The frequency of driving route use is used to describe the familiarity of drivers with road conditions. If the driving routes are very scattered and there are no high-frequency routes, it can be inferred that the driver is unfamiliar with the road conditions. (2) When the total weight of a vehicle and its cargo is greater than the upper limit of the total weight of the vehicle and its cargo, the vehicle can be judged as overloaded. The upper limit of the total weight of the vehicle and its cargo corresponds to the vehicle type. When a vehicle is judged as overloaded, and the total weight of the vehicle and its cargo is not consistent with the over limit permit, the vehicle is considered illegal to drive. (3) When the actual travel time is less than the minimum travel time, it can be inferred that the vehicle has a risk of fatigued driving, driving over the speed limit, fake license plate, or other risks. The minimum travel time consists of the lower limit of the driving time and the minimum rest time. The lower limit of the driving time is equal to the driving mileage divided by the upper limit of the driving speed. Through the above analysis, it is possible to understand the driving risks of drivers and provide a scientific basis for analyzing dangerous or illegal driving.

2.2. Driving Route

The frequency of driving route use is used to describe the familiarity of drivers with road conditions. If the driving routes are very scattered and there are no high-frequency routes, it can be inferred that the driver is unfamiliar with the road conditions.

Define $r(i,j)$ as the sequence of driving routes between entrance toll station i and exit toll station j for a vehicle. $N_{i,j}$ represents the number of driving routes between entrance toll station i and exit toll station j for a vehicle. Then,

$$r(i,j) = \left\{ r_{i,j}^{1}, r_{i,j}^{2}, \cdots, r_{i,j}^{N_{i,j}} \right\} \tag{1}$$

where $r_{i,j}^{N_{i,j}}$ is the $\left(N_{i,j}\right)^{th}$ driving route between entrance toll station i and exit toll station j.

Define R as all sequences of driving routes between all entrance toll stations and exit toll stations for a vehicle. Then,

$$R = \{r(1,1), \cdots, r(i,j), \cdots, r(I,J)\} = \left\{ \begin{array}{c} \left\{ r_{1,1}^{1}, r_{1,1}^{2}, \cdots, r_{1,1}^{N_{1,1}} \right\}, \\ \cdots, \\ \left\{ r_{i,j}^{1}, r_{i,j}^{2}, \cdots, r_{i,j}^{N_{i,j}} \right\}, \\ \cdots, \\ \left\{ r_{I,J}^{1}, r_{IJ}^{2}, \cdots, r_{I,J}^{N_{I,J}} \right\} \end{array} \right\} \tag{2}$$

where I and J are the number of entrance toll stations and exit toll stations, respectively. $i = 1, 2, \cdots, I$ and $j = 1, 2, \cdots, J$.

Define N_{all} as the total number of all driving routes for a vehicle. Then, $N_{all} = \sum_{j=1}^{J} \sum_{i=1}^{I} N_{i,j}$. Define $\rho_{i,j}$ as the proportion of driving routes between entrance toll station i and exit toll station j for a vehicle. Thus,

$$\rho_{i,j} = \frac{N_{i,j}}{N_{all}} = \frac{N_{i,j}}{\sum_{j=1}^{J} \sum_{i=1}^{I} N_{i,j}} \tag{3}$$

Define ϵ as the threshold to judge if a route is familiar or not. When the number of driving routes between an entrance toll station and exit toll station for a vehicle is not greater than ϵ, the route is defined to be unfamiliar to the driver. $N_{i,j}$ is the number of driving routes between entrance toll station i and exit toll station j for a vehicle. Thus, if $N_{i,j} \leq \epsilon$, the driver is unfamiliar with the route between entrance toll station i and exit toll station j. Normally, $\epsilon = 1$.

$\alpha_{unfamiliar}^{i,j}$ represents whether the driver is unfamiliar with the route between entrance toll station i and exit toll station j. $\alpha_{unfamiliar}^{i,j} = 1$ indicates that the driver is unfamiliar with the route between entrance toll station i and exit toll station j. $\alpha_{unfamiliar}^{i,j} = 0$ indicates that the driver is familiar with the route between entrance toll station i and exit toll station j. Thus,

$$\alpha_{unfamiliar}^{i,j} = \begin{cases} 1, & N_{i,j} \le \epsilon \\ 0, & N_{i,j} > \epsilon \end{cases} \tag{4}$$

2.3. Overload

From highway toll data, vehicle types, the number of axels, and the total weight of vehicles and their cargo can be obtained. The upper limit of the total weight of the vehicle and its cargo corresponds to the vehicle type and the number of the axles, which is shown in Table 1 [34]. When the total weight of a vehicle and its cargo is greater than the upper limit of the total weight of the vehicle and its cargo, the vehicle is identified as overloaded.

Table 1. The upper limits of the total weights of vehicles and their cargo.

Vehicle Type	Upper Limit of Total Weight of Vehicle and Its Cargo (Tons)
Two-axle truck	18
Three-axle truck	25
Three-axle trailer combination	27
Four-axle truck	31
Four-axle trailer combination	36
Five-axle trailer combination	43
Six-or-more-axle single-trailer truck	46
Six-or-more-axle trailer combination	49

Vehicle types include two-axle trucks, three-axle trucks, three-axle trailer combination, four-axle trucks, four-axle trailer combination, five-axle trailer combination, six-or-more-axle single-trailer truck, and six-or-more-axle trailer combination. The corresponding upper limits of the total weights of the vehicles and their cargo are 18, 25, 27, 31, 36, 43, 46, and 49 tons, respectively [34]. For example, when a vehicle is a two-axle truck, the upper limit of the total weight of the vehicle and its cargo is 18 tons. When a vehicle is a six-axle trailer combination, the upper limit of the total weight of the vehicle and its cargo is 49 tons.

Define ω as the total weight of the vehicle and its cargo. $\overline{\omega}_\tau$ represents the upper limit of the total weight of the vehicle and its cargo when the vehicle type is τ. $\alpha_{overload}$ represents whether the vehicle is overloaded. $\alpha_{overload} = 1$ indicates that the vehicle is overloaded. $\alpha_{overload} = 0$ indicates the vehicle is not overloaded. The criterion for determining overload is that the total weight of the vehicle and its cargo is greater than the upper limit of the total weight of the vehicle and its cargo. Thus,

$$\alpha_{overload} = \begin{cases} 1, & \omega > \overline{\omega}_\tau \\ 0, & \omega \le \overline{\omega}_\tau \end{cases} \tag{5}$$

When a vehicle is judged as overloaded, and the total weight of the vehicle and its cargo is not consistent with the over-limit permit, the vehicle is considered illegal to drive.

The process for identifying overload is shown in Figure 3.

2.4. Travel Time

When the actual travel time of a vehicle is less than the minimum travel time, it can be inferred that the vehicle has a risk of dangerous or illegal driving behavior, such as fatigued driving, driving over the speed limit, or a fake license plate.

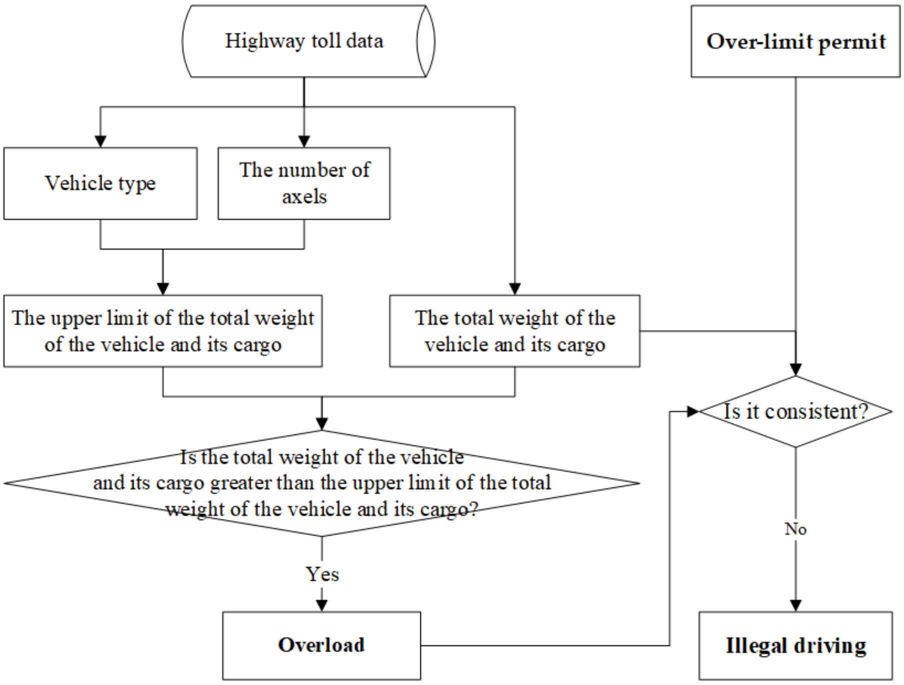

Figure 3. The process for identifying overload.

It is worth noting that fatigued driving, driving above the speed limit, and fake license plates are different factors that may lead to a decrease in travel time. For fatigued driving, a decrease in the total travel time is caused by a decrease in rest time. For driving above the speed limit, a decrease in the total travel time is caused by exceeding the legal driving speed. For fake license plates, two different vehicles with the same license plate appear in different positions within a short period of time, resulting in an abnormal driving time. Although the reasons are different, they are considered dangerous or illegal driving behaviors, resulting in reduced travel time.

The minimum travel time consists of the lower limit of the driving time and the minimum rest time. Define t_{total}^{min} as the minimum travel time. t_{drive}^{min} represents the lower limit of the driving time. t_{rest}^{min} denotes the minimum rest time. Then,

$$t_{total}^{min} = t_{drive}^{min} + t_{rest}^{min} \tag{6}$$

The lower limit of the driving time is equal to the driving mileage divided by the upper limit of the driving speed. L represents the driving mileage (km). V_{drive}^{max} represents the upper limit of the driving speed (km/h). Then,

$$t_{drive}^{min} = \frac{L}{V_{drive}^{max}} \tag{7}$$

Measures for the Scoring Management of Road Traffic Safety Violations [35] stipulates that the continuous driving time shall not exceed 4 h (h) without rest and each rest time shall not be less than 20 min. Define φ as the maximum allowable continuous driving time. Δ_{rest}^{min} represents the minimum rest time for each rest. Thus, $\varphi = 4$ h, $\Delta_{rest}^{min} = 20$ min = 0.333 h. t_{drive} represents the expected travel time. N_{rest}^{min} represents the minimum rest number. $\lfloor \cdot \rfloor$ represents rounding down. Then,

$$N_{rest}^{min} = \left\lfloor \frac{t_{drive}}{\varphi} \right\rfloor \tag{8}$$

t_{rest}^{min} is equal to N_{rest}^{min} multiplied by Δ_{rest}^{min}. Thus,

$$t_{rest}^{min} = N_{rest}^{min} \cdot \Delta_{rest}^{min} \tag{9}$$

From Formulas (6)–(9), the following formula can be obtained:

$$t_{total}^{min} = \frac{L}{V_{drive}^{max}} + \left\lfloor \frac{t_{drive}}{\varphi} \right\rfloor \cdot \Delta_{rest}^{min} \tag{10}$$

t_{actual} represents the actual travel time. β_{risk} represents whether the vehicle has a risk of fatigued driving, driving over the speed limit, a fake license plate, or other risks. $\beta_{risk} = 1$ indicates the risk of fatigued driving, driving over the speed limit, a fake license plate, or other risks. $\beta_{risk} = 0$ means there is no risk of fatigued driving, driving over the speed limit, a fake license plate, or other risks. Thus,

$$\beta_{risk} = \begin{cases} 1, & t_{actual} < t_{total}^{min} \\ 0, & t_{actual} \geq t_{total}^{min} \end{cases} \tag{11}$$

The method for identifying the risks of fatigued driving, driving over the speed limit, fake license plates, or other risks is shown in Figure 4.

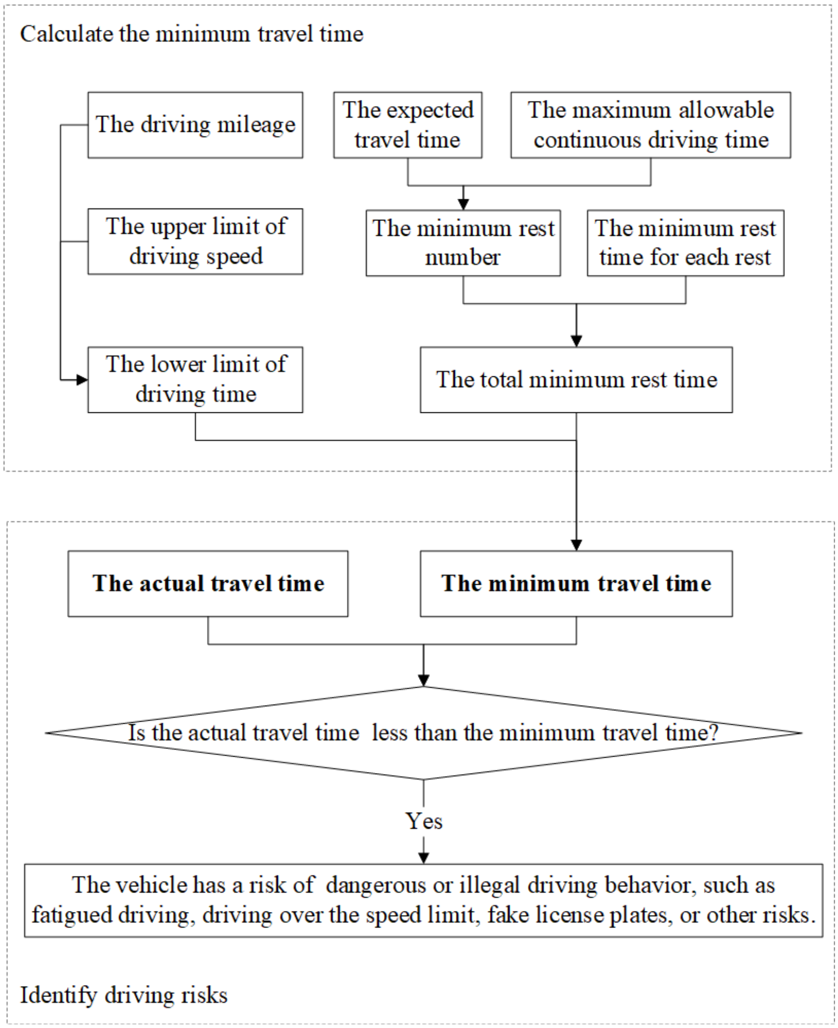

Figure 4. The method for identifying the risk of fatigued driving, driving over the speed limit, fake license plates, or other risks.

3. Case Study

A traffic accident that occurred on 26 March 2022 was used to demonstrate the process of the proposed framework for identifying driving risks based on highway toll data. In the traffic accident, two trucks collided. The first truck was a two-axle truck, and its driving route was from the Shandong Xinxian entrance toll station to the Liaoning Xingcheng exit toll station. The second truck was a six-axle trailer combination, and its driving route was from the Inner Mongolia Hohhot South entrance toll station to the Liaoning Jinzhou East exit toll station. The characteristics of the two trucks were analyzed based on highway toll data from 1 January 2021 to 30 March 2022. The threshold to judge if a route is familiar or not was set to 1, i.e., $\epsilon = 1$.

3.1. The First Truck

Figure 5 shows the driving routes of the first truck from 1 January 2021 to 25 March 2022 before the accident occurred. The maximum proportion of driving routes was 3.14%. That is, from the Shandong Hedian entrance toll station to the Liaoning Chaoyang exit toll station, there were seven driving routes for the first truck from 1 January 2021 to 25 March 2022, i.e., $N_{i,j} = 7$. There were 223 driving routes in total for the first truck from 1 January 2021 to 25 March 2022, i.e., $N_{all} = 223$. Therefore, the proportion of driving routes from the Shandong Hedian entrance toll station to the Liaoning Chaoyang exit toll station was $\rho_{i,j} = \frac{N_{i,j}}{N_{all}} = \frac{7}{223} = 3.14\%$.

The accident route on 26 March 2022 for the first truck was from the Shandong Xinxian entrance toll station to the Liaoning Xingcheng exit toll station. Before the accident occurred, there was no driving route for the first truck from Shandong Xinxian Station to Liaoning Xingcheng Station from 1 January 2021 to 25 March 2022, i.e., $N_{i,j} = 0$, which was less than the threshold $\epsilon = 1$, i.e., $N_{i,j} = 0 < \epsilon = 1$. Based on Formula (4), $\alpha^{i,j}_{unfamiliar} = 1$, indicating that the driver was unfamiliar with the road conditions of the accident route.

Figure 6 shows the total weights of the first truck and its cargo from 1 January 2021 to 30 March 2022. The number of axles varied for different trips. For most trips, it had two axles, while for a small number of trips, it had three, four, or six axles.

The upper limit of the total weight of the vehicle and its cargo corresponds to the number of axles (see Table 1). In the collision accident, the number of axles of the first truck was two. Thus, the upper limit of the total weight of the vehicle and its cargo was 18 tons, i.e., $\overline{\omega}_\tau = 18$ tons. The total weight of the vehicle and its cargo was 13.321 tons on the traffic accident day, i.e., $\omega = 13.321$ tons. The total weight of the vehicle and its cargo was less than the upper limit of the total weight of the vehicle and its cargo, i.e., $\omega = 13.321$ tons $< \overline{\omega}_\tau = 18$ tons. Based on Formula (5), $\alpha_{overload} = 0$, indicating that the first truck was not overloaded on the traffic accident day.

The travel time of the first truck from 1 January 2021 to 30 March 2022 is shown in Figure 7. The first truck had a total of 284 driving routes from 1 January 2021 to 30 March 2022. On the traffic accident day, the actual travel time was $t_{actual} = 37.71$ h, and the minimum travel time was $t^{min}_{total} = 9.47$ h, i.e., $t_{actual} > t^{min}_{total}$. Based on Formula (11), $\beta_{risk} = 0$, indicating that the first truck had no risk of fatigued driving, driving over the speed limit, or a fake license plate.

3.2. The Second Truck

Figure 8 shows the driving routes of the second truck from 1 January 2021 to 25 March 2022. The second truck had 414 trips from 1 January 2021 to 25 March 2022. The maximum proportion of driving routes was 3.14%. For example, from the Lutai West entrance toll station to the Zhaojun exit toll station, there were 13 driving routes for the second truck from 1 January 2021 to 25 March 2022, i.e., $N_{i,j} = 13$. There were 414 driving routes in total for the second truck from 1 January 2021 to 25 March 2022, i.e., $N_{all} = 414$. The proportion of driving routes from the Lutai West entrance toll station to the Zhaojun exit toll station was $\rho_{i,j} = \frac{N_{i,j}}{N_{all}} = \frac{13}{414} = 3.14\%$.

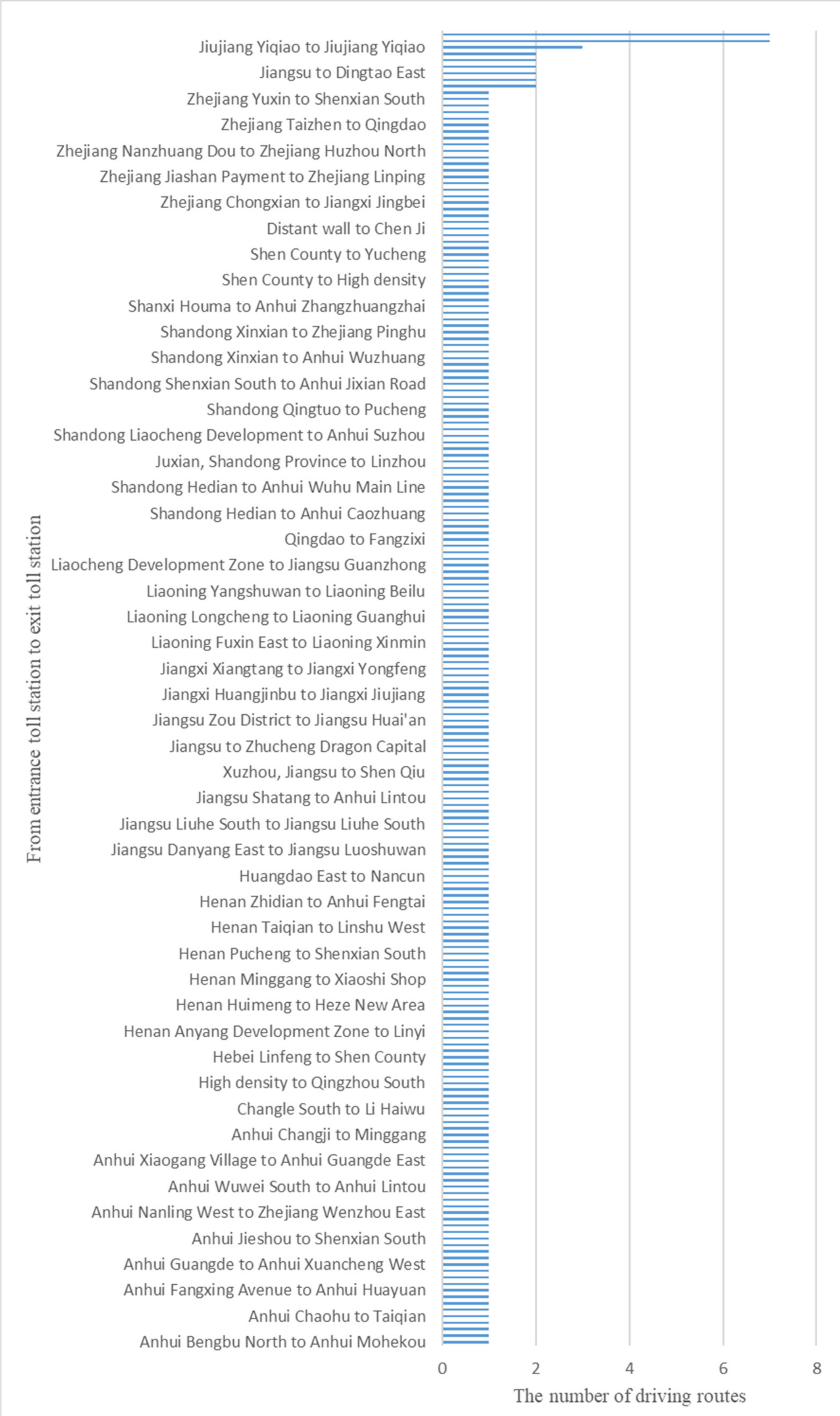

Figure 5. The driving routes of the first truck from 1 January 2021 to 25 March 2022 before the accident occurred.

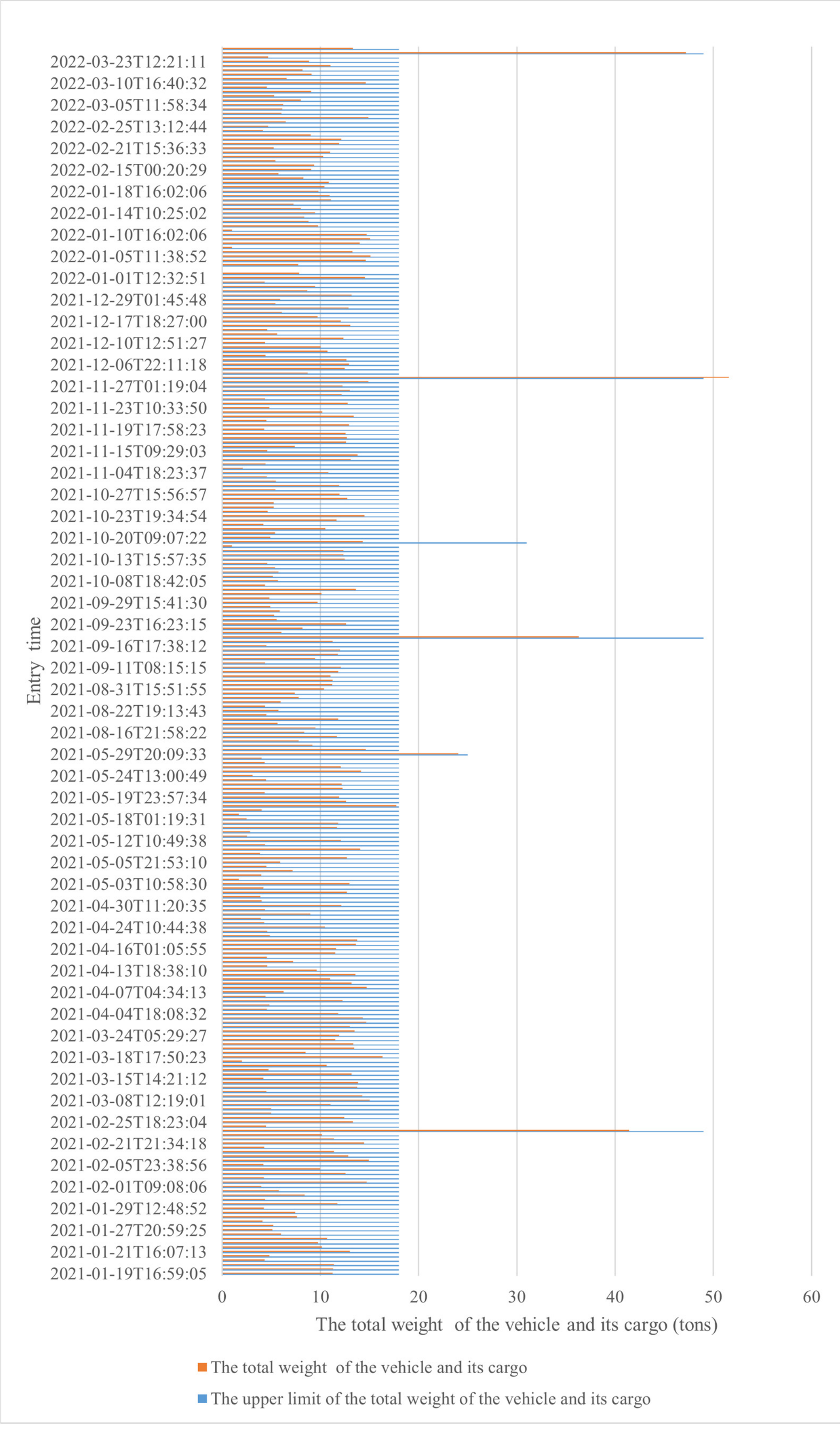

Figure 6. The total weight of the first truck and its cargo from 1 January 2021 to 30 March 2022.

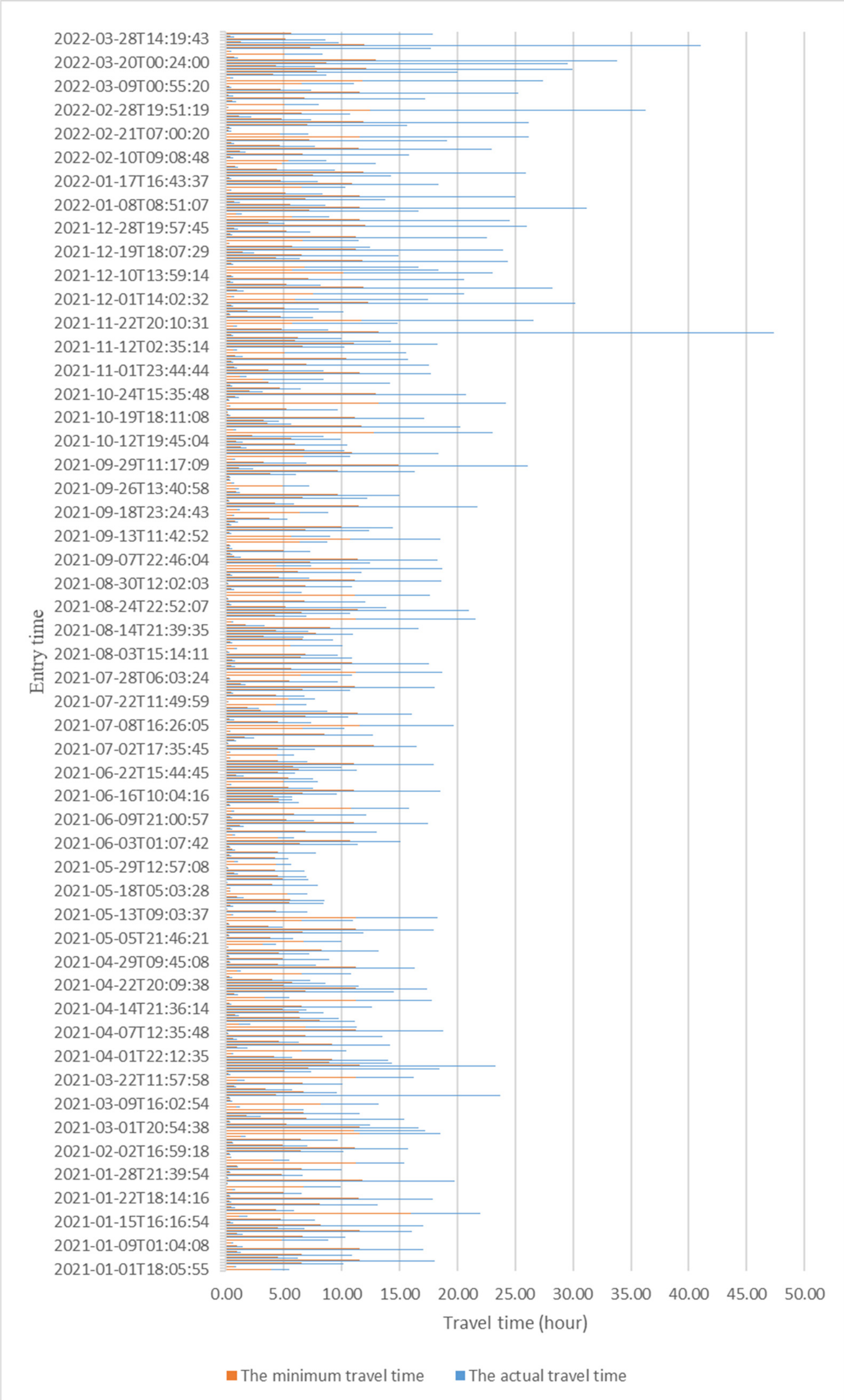

Figure 7. Travel time of the first truck from 1 January 2021 to 30 March 2022.

The accident route on 26 March 2022 for the second truck was from the Inner Mongolia Hohhot South entrance toll station to the Liaoning Jinzhou East exit toll station. Before the accident occurred, there was only one driving route for the second truck from Inner Mongolia Hohhot South Station to Liaoning Jinzhou East Station from 1 January 2021 to 25 March 2022, i.e., $N_{i,j} = 1$, which was not greater than the threshold $\epsilon = 1$, i.e., $N_{i,j} = \epsilon$. Based on Formula (4), $\alpha^{i,j}_{unfamiliar} = 1$, indicating that the driver was unfamiliar with the road conditions of the accident route, which was an important reason for the traffic accident.

Figure 9 shows the total weight of the second truck and its cargo from 1 January 2021 to 30 March 2022. As it was a six-axle trailer combination on the accident day, the upper limit of the total weight of the vehicle and its cargo was 49 tons (see Table 1), i.e., $\overline{\omega}_\tau = 49$ tons. The total weight of the vehicle and its cargo was 48 tons on the accident day, i.e., $\omega = 48$ tons. The total weight of the vehicle and its cargo was less than the upper limit of the total weight of the vehicle and its cargo, i.e., $\omega = 48$ tons $< \overline{\omega}_\tau = 49$ tons. Based on Formula (5), $\alpha_{overload} = 0$, indicating that the second truck was not overloaded on the traffic accident day.

The travel time of the second truck from 1 January 2021 to 30 March 2022 is shown in Figure 10. The second truck had a total of 419 driving routes from 1 January 2021 to 30 March 2022. For all driving routes, the actual travel time was greater than the minimum travel time. On the traffic accident day, the actual travel time was $t_{actual} = 41.02$ h, and the minimum travel time was $t^{min}_{total} = 11.98$ h, i.e., $t_{actual} > t^{min}_{total}$. Based on Formula (11), $\beta_{risk} = 0$, indicating that the second truck had no risk of fatigued driving, driving over the speed limit, or a fake license plate.

3.3. Cause Analysis

Based on the above analysis, the causes of the traffic accident could be identified by analyzing driving risks of the two trucks. On the accident day, the vehicle types of the two trucks were a two-axle truck and a six-axle trailer combination, respectively.

Before the accident occurred, there was no driving route for the two-axle truck from Shandong Xinxian Station to Liaoning Xingcheng Station from 1 January 2021 to 25 March 2022, indicating that the driver was unfamiliar with the road conditions of the accident route. The total weight of the vehicle and its cargo was less than the upper limit of the total weight of the vehicle and its cargo on the traffic accident day. The actual travel time was greater than the minimum travel time, indicating that the two-axle truck had no risk of fatigued driving, driving over the speed limit, or a fake license plate. Thus, for the first truck, the driver's unfamiliarity with the road conditions of the accident route was a significant reason for the accident.

For the second truck, there was only one driving route from Inner Mongolia Hohhot South Station to Liaoning Jinzhou East Station from 1 January 2021 to 25 March 2022, indicating that the driver was also unfamiliar with the road conditions of the accident route. The total weight of the vehicle and its cargo was less than the upper limit of the total weight of the vehicle and its cargo on the traffic accident day. The actual travel time was greater than the minimum travel time, indicating that the second truck had no risk of fatigued driving, driving over the speed limit, or a fake license plate. Thus, for the second truck, the driver's unfamiliarity with the road conditions of the accident route was a significant reason for the accident.

In summary, the drivers' unfamiliarity with the road conditions of the accident route was the main cause of the traffic accident.

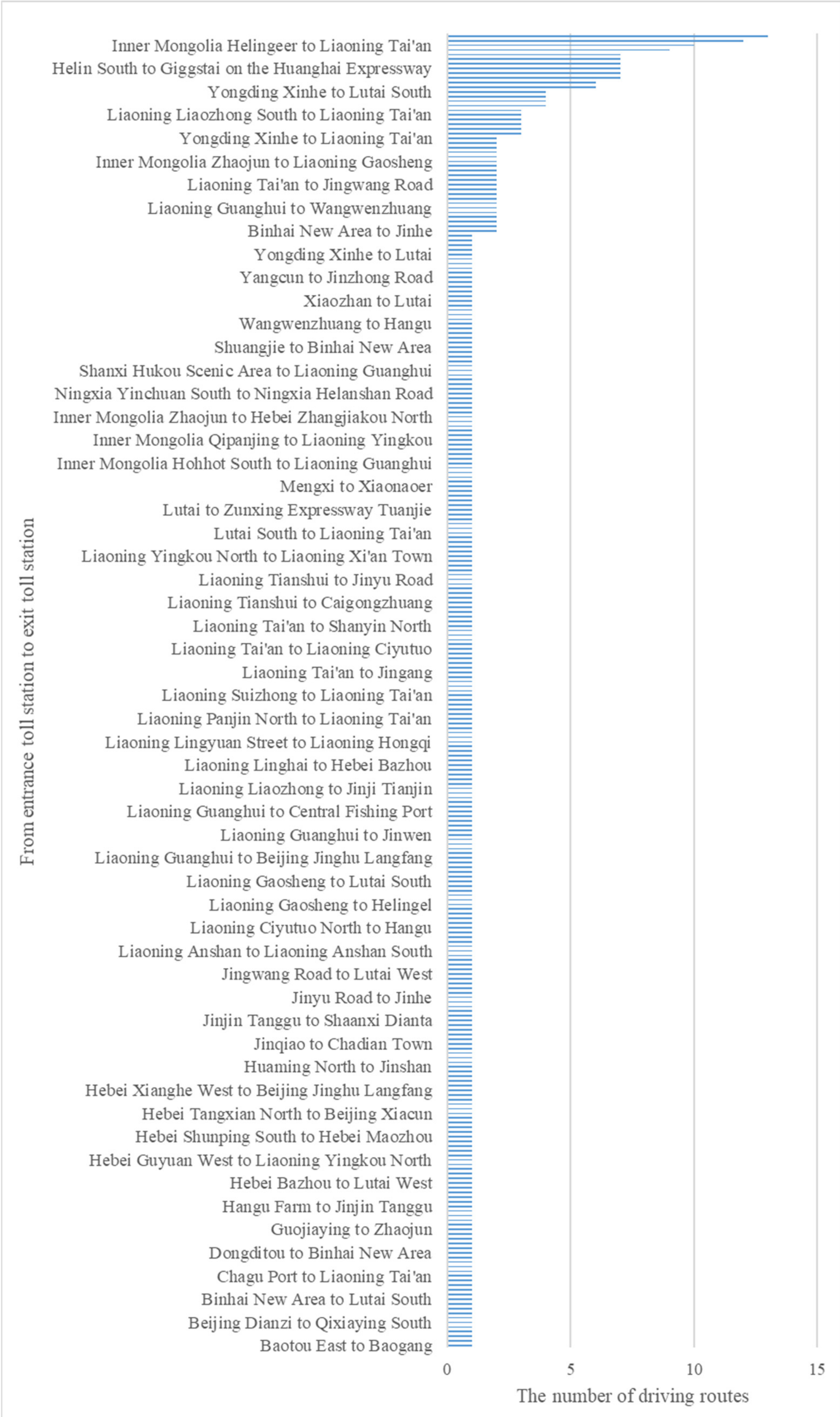

Figure 8. The driving routes of the second truck from 1 January 2021 to 25 March 2022.

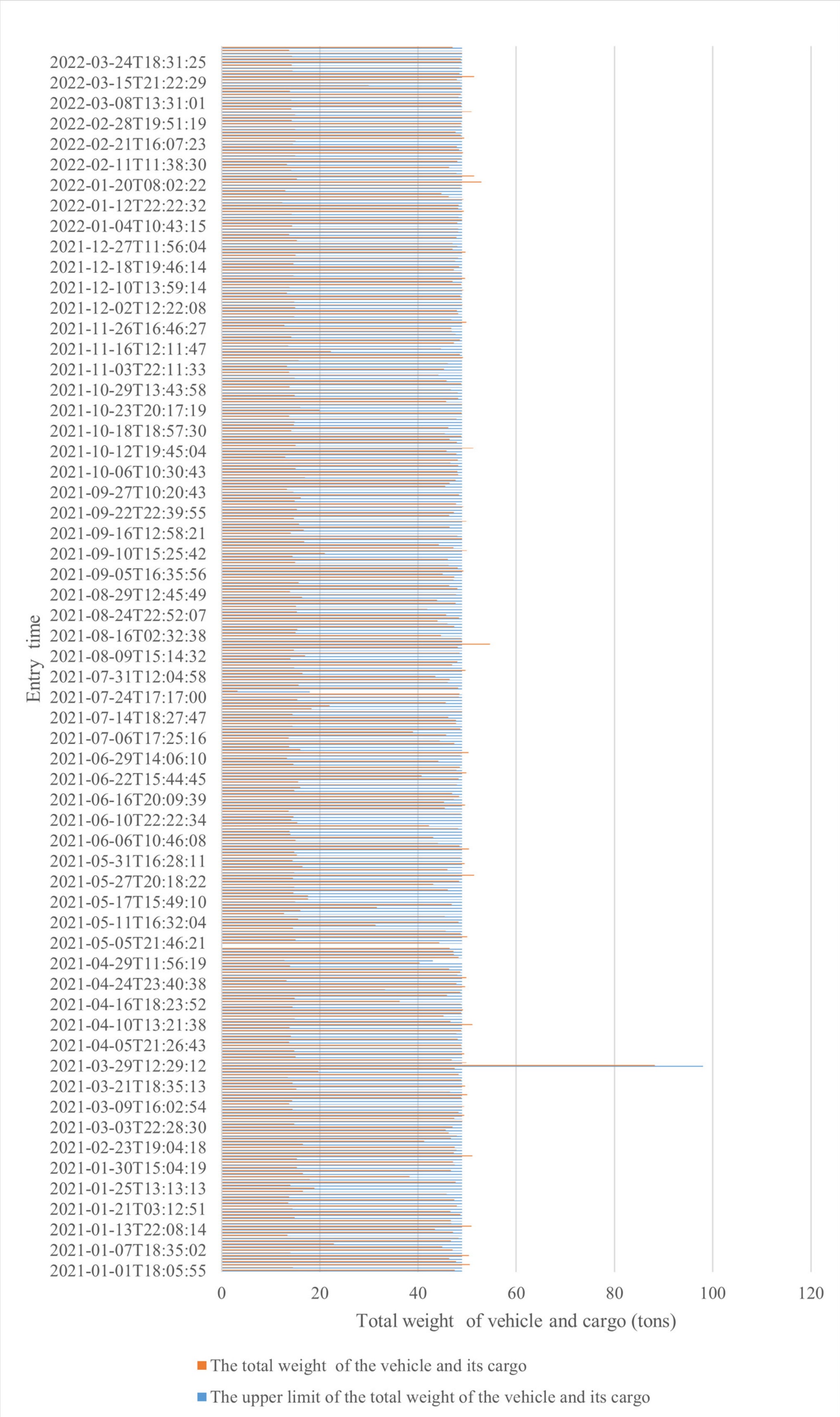

Figure 9. The total weight of the second truck and its cargo from 1 January 2021 to 30 March 2022.

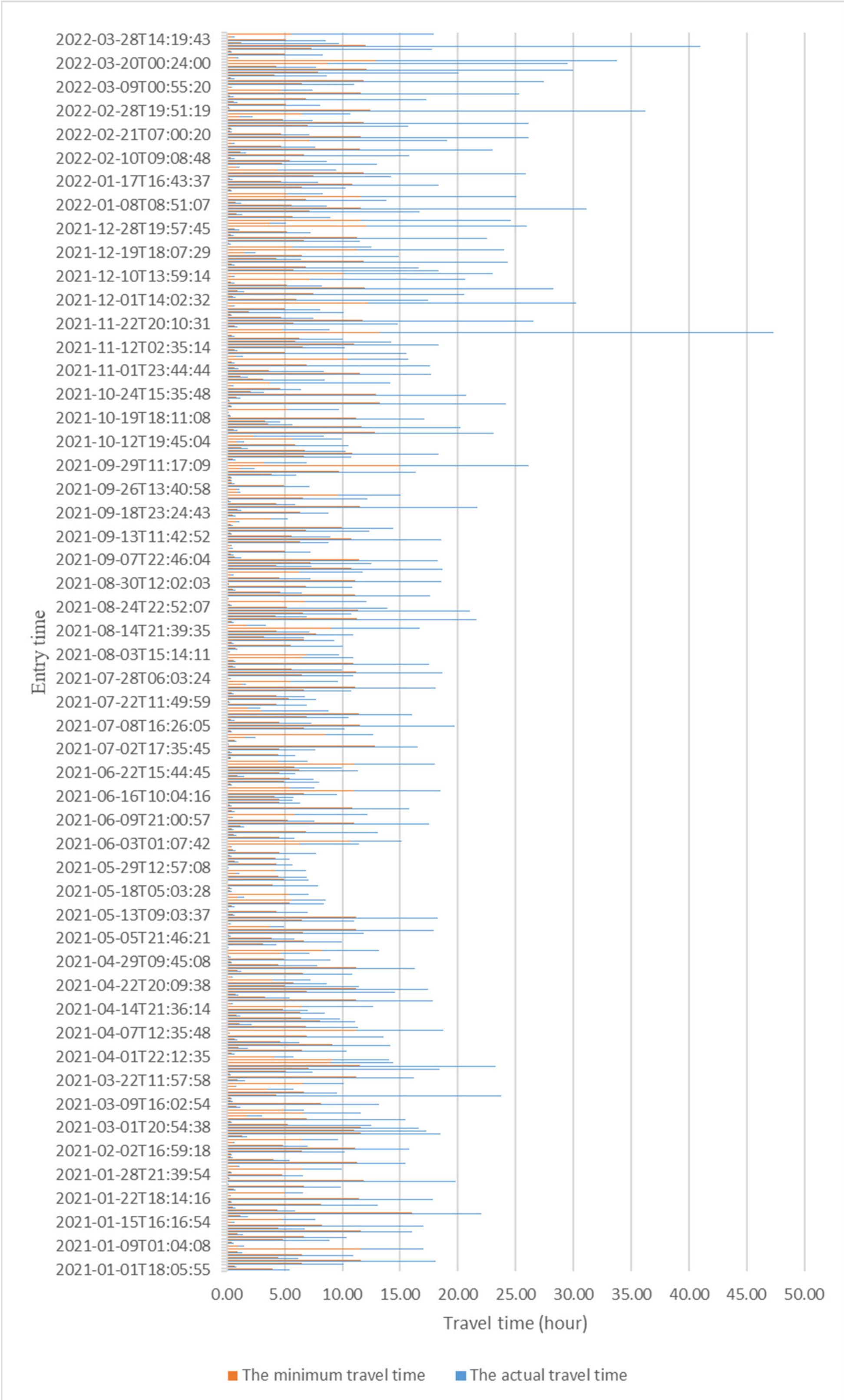

Figure 10. Travel time of the second truck from 1 January 2021 to 30 March 2022.

4. An Additional Application

In cooperation with the Highway Monitoring & Response Center in China (i.e., HMRC) and Liaoning Expressway Operation Management Co., Ltd. (Liaoning, China), a portrait system based on highway toll data was proposed to analyze travel characteristics, including driving routes, overload, travel time, etc. With these characteristics, abnormally driven vehicles can be detected. In this section, the key results for an additional application to a ramp bridge rollover accident are outlined.

4.1. Accident Description

Based on highway toll data (i.e., the license plate recognition data from toll gantries), the actual driving route of the vehicle was obtained. As show in Figure 11, the vehicle departed from the Lintong Toll Station in Shaanxi Province but did not exit the Lianhuo Expressway at the Qindong Toll Station. Instead, it passed through the Weiyu Expressway to the Shanghai Shaanxi Expressway and entered Henan Province. Due to the absence of toll stations between provincial boundaries, the vehicle drove all the way along the Daguang Expressway to Hubei Province and overturned at the Huahu Interchange. The over-limit permit shows that the vehicle obtained an over-limit permit for the transportation of large items from Lintong Toll Station to Qindong Toll Station [36]. The vehicle did not follow the permitted route, which was illegal and over the transportation limit.

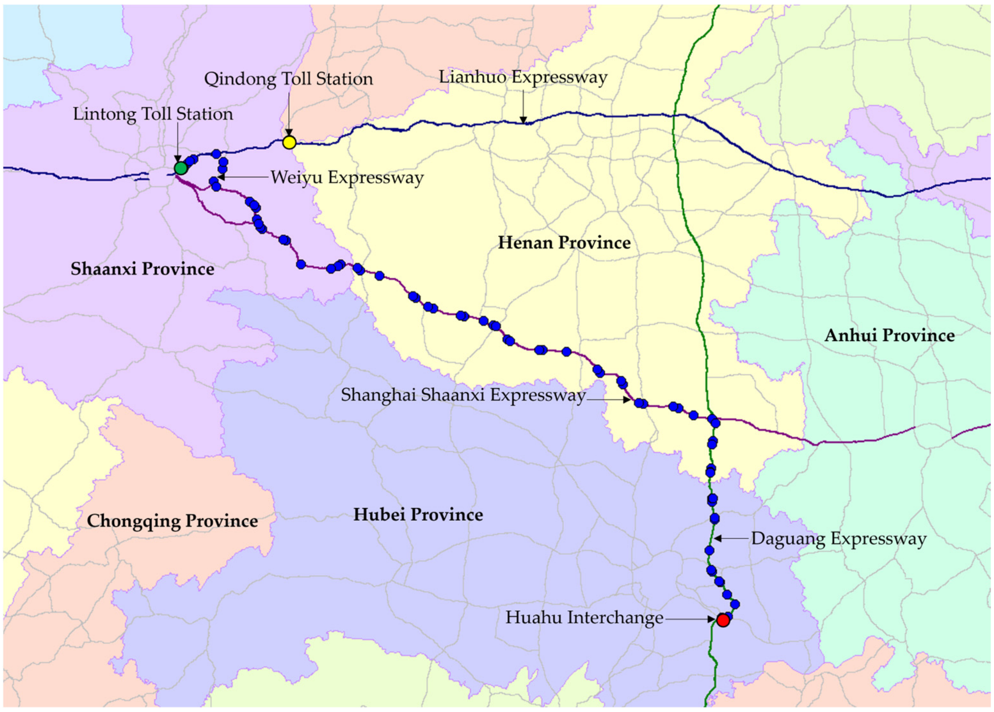

Figure 11. The driving route of the accident vehicle based on highway toll data. Note: (1) The red dot represents the Huahu Interchange. The green dot represents the Lintong Toll Station. The yellow dot represents the Qindong Toll Station. The dark blue dots indicate the trajectory of the vehicle passing through the toll gantries. (2) The dark blue lines represent the Lianhuo Expressway. The deep purple lines represent the Shanghai Shaanxi Expressway. The green lines represent the Daguang Expressway. The gray lines indicate other highways. (3) Different colored areas represent different provinces, that is, the light purple area represents Shaanxi Province, the medium purple area represents Hubei Province, the light yellow area represents Henan Province, and the light green area represents Anhui Province.

4.2. Driving Route Result

The driving routes of the accident vehicle from 1 January 2021 to 13 December 2021 are shown in Table 2. The accident vehicle had only one or two driving routes between each entrance toll station and exit toll station from 1 January 2021 to 13 December 2021, and the maximum proportion of driving routes was 16.67%. That is, from the Shaanxi

Xizhangbao entrance toll station to the Shaanxi Liucunbao exit toll station, there were two driving routes for the accident vehicle, i.e., $N_{i,j} = 2$. The total number of all driving routes for the accident vehicle was 12, i.e., $N_{all} = 12$. The proportion of driving routes from the Shaanxi Xizhangbao entrance toll station to the Shaanxi Liucunbao exit toll station was $\rho_{i,j} = \frac{N_{i,j}}{N_{all}} = \frac{2}{12} = 16.67\%$.

Table 2. The driving routes of the accident vehicle from 1 January 2021 to 13 December 2021.

Entrance Toll Station	Exit Toll Station	Trip Number	Proportion
Shaanxi Xizhangbao Toll Station	Shaanxi Liucunbao Toll Station	2	16.67%
Chen Guantun Toll Station	Shaanxi Kaikou Toll Station	1	8.33%
Huamingnan Toll Station	Jingwang Road Toll Station	1	8.33%
Jinjin Tanggu Toll Station	Hebei Fengning Toll Station	1	8.33%
Jinjin Tanggu Toll Station	Jingwang Road Toll Station	1	8.33%
Jingwang Road Toll Station	Hebei Xushui Station	1	8.33%
Jingwang Road Toll Station	Huamingnan Toll Station	1	8.33%
Jingwang Road Toll Station	Sun Village East Toll Station	1	8.33%
Shaanxi Liucunbao Toll Station	Shaanxi Xizhangbao Toll Station	1	8.33%
Shanghai Jianchuan Road Toll Station	Shanghai Zhuanqiao Toll Station	1	8.33%
Yangling Toll Station	G1503 Wenchuan Road Toll Station	1	8.33%

The accident route on 14 December 2021 for the accident vehicle was from the Lintong Toll entrance toll station in Shaanxi Province to the Huahu Interchange in Hubei Province. Before the accident occurred, there was no driving route for the accident vehicle from Lintong Toll Station to the Huahu Interchange from 1 January 2021 to 13 December 2021, i.e., $N_{i,j} = 0$, which is less than the threshold $\epsilon = 1$, i.e., $N_{i,j} = 0 < \epsilon = 1$. Based on Formula (4), $\alpha^{i,j}_{unfamiliar} = 1$, indicating that the driver was unfamiliar with the road conditions of the accident route.

4.3. Overload Result

From the highway toll data of the entrance toll station, it could be seen that the vehicle was a six-or-more-axle trailer combination. Thus, the upper limit of the total weight of the vehicle and its cargo was 49 tons, i.e., $\overline{\omega}_{\tau} = 49$ tons. The total weight of the vehicle and its cargo was 198 tons on the traffic accident day (see Table 3), i.e., $\omega = 198$ tons. The total weight of the vehicle and its cargo was greater than the upper limit of the total weight of the vehicle and its cargo, i.e., $\omega = 198$ tons $> \overline{\omega}_{\tau} = 49$ tons. Based on Formula (5), $\alpha_{overload} = 1$, indicating that the first truck was overloaded on the traffic accident day. The vehicle was severely overloaded, resulting in the bridge rollover accident.

Table 3. The total weight of the vehicle and its cargo.

Vehicle Type	Entrance Weight (tons)	Entrance Time
Six-or-more-axle trailer combination	198	2021-12-14T10:36:26

4.4. Travel Time Result

The entrance time of the truck at Lintong Toll Station in Shaanxi Province was 10:36:26 on 14 December 2021. The truck arrived at the Huahu Interchange at 15:25:33 on 18 December 2021, which was the last transaction record of the toll gantry. The actual travel time $t_{actual} = 100.82$ h, and the minimum travel time $t^{min}_{total} = 11.98$ h, i.e., $t_{actual} > t^{min}_{total}$. Based on Formula (11), $\beta_{risk} = 0$, indicating that the truck had no risk of fatigued driving, driving over the speed limit, or a fake license plate.

4.5. Cause Analysis

The statistical results indicate that the driving routes of the accident vehicle were scattered and there were no high-frequency routes. The vehicle had never driven along the accident route from Lintong Toll Station in Shaanxi Province to the Huahu Interchange in Hubei Province. The driver's unfamiliarity with the road conditions was an important reason for the traffic accident. The total weight of the vehicle and its cargo was 198 tons, which was greater than the upper limit of the total weight of the vehicle and its cargo. The vehicle was severely overloaded, resulting in the bridge rollover accident. The actual travel time was greater than the minimum travel time, indicating that the vehicle had no risk of fatigued driving, driving over the speed limit, or a fake license plate. Thus, the driver's unfamiliarity with the road conditions and overload were the main causes of this accident.

5. Conclusions

This paper proposes an analytical framework based on highway toll data to identify dangerous or illegal driving risks, such as unfamiliarity with road conditions, overload, driving over the speed limit, fatigued driving, fake license plates, or other risks. Unfamiliarity with road conditions is identified based on low use frequency of the driving route. When the total weight of the vehicle and its cargo is greater than the upper limit of the total weight of the vehicle and its cargo, the vehicle is judged to be overloaded. When the actual travel time is less than the minimum travel time, it can be inferred that the vehicle has a risk of fatigued driving, driving over the speed limit, a fake license plate, or other risks.

Two accidents were used to demonstrate the process of the proposed framework for identifying driving risks based on highway toll data. The analysis results show that the main causes of the traffic accidents were the drivers' unfamiliarity with the road conditions and overload. The case studies prove that the proposed framework can effectively identify dangerous and illegal driving risks, providing a scientific basis for analyzing the causes of traffic accidents. Although fatigued driving, driving over the speed limit, and fake license plates were not the causes in the case studies, the analysis results provide a clear conclusion on dangerous and illegal driving risks.

The purpose of this paper was to identify the driving risks of truck drivers based on highway toll data. The study proposes a set of ideas for constructing vehicle portrait indicators to identify driving risks and provides a scientific basis for the warning and prevention of dangerous and illegal driving risks. When identifying driving risks, traffic management departments can take control measures and remind drivers through different information dissemination channels. For example, if an overloaded vehicle has an over-limit permit, the permitted route can be obtained through the over-limit permit. If the actual driving route does not match the over-limit permit, it is considered illegal driving. The management department can take control measures against overloaded and illegal vehicles and issue high-risk vehicle monitoring warnings.

Despite some achievements, there are still some limitations in this study. Several extensions are worth exploring in future work.

(1) There are many other causes for traffic accidents according to the statistics of actual traffic accident cases, such as drunk driving, illegal overtaking, illegal passing, illegal reversing, illegal lane changing, illegal parking, illegal turning, illegal grabbing, reverse driving, not yielding according to regulations, failure to maintain a safe distance, etc. These factors can be incorporated into accident cause analysis in the future research.

(2) Fatigue and driving above the speed limit are two different factors that can contribute to accidents. However, both fatigued driving and driving above the speed limit can reduce travel time. For fatigued driving, a decrease in the overall travel time is caused by a decrease in rest time. For driving above the speed limit, a decrease in the overall travel time is caused by exceeding the legal driving speed. Although the reasons are different, they are considered dangerous driving behaviors, the result of which is a reduction in travel time. However, speeding and having a long rest may result in a

normal total travel time, which is an uncertain risk and not considered in this study. This uncertain risk can be studied in future research.

(3) Overload may cause the collapse of an entire bridge, causing serious casualties and economic losses. However, the transportation of large items is an important part of supporting major national engineering projects, such as transformers in substations, generator stators in power plants, and reactors in chemical plants, which makes it unavoidable for overweight vehicles to travel on the road. Therefore, monitoring and warning overweight vehicles and providing reasonable driving routes are of great significance for improving the safety of road traffic systems. Future work can study the risk assessment factors of bridges and establish path guidance models and algorithms for overweight vehicles to enhance the resilience of transportation hubs.

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