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Research Article

Off-Ramp Vehicle Mandatory Lane-Changing Duration in Small Spacing Section of Tunnel-Interchange Section Based on Survival Analysis

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Due to topography, geology, and other factors, small spacing sections are common between tunnels and interchange exits. There is mandatory lane-changing behavior for vehicles that need to leave the main line and drive inside the road before leaving the tunnel. Affected by the “white hole” of a tunnel, the lane-changing behavior of off-ramp vehicles differs significantly from that of original roadbed sections. To study the mandatory lane-changing duration (MLCD) of off-ramp vehicles in small spacing sections of the tunnel to interchange in mountainous areas, their time and trajectory data were collected based on a driving simulator. According to the characteristics of the data, the survival analysis method was used to analyze the influence on the MLCD of off-ramp vehicles of the spacing section between the tunnel and interchange, vehicle types, tunnel types, ramp types, highway service level, and whether to set exit advance guide signs in the tunnel and the Cox proportional hazards model of the MLCD was established. The results showed that the spacing of the tunnel interchange, the road service level, and whether to set exit advance guide signs in the tunnel had significant effects on the MLCD of vehicles, while the vehicle, the tunnel, and the ramp types did not. When the spacing section of the tunnel interchange was less than 500 m, the off-ramp vehicle had continuous mandatory lane-changing behavior, and when the distance decreased from 400 m to 300 m, the risk rate of lane changing increased by 5.68 times. Survival function curve estimation provided the 75% quantile of MLCD of off-ramp vehicles under different conditions, which could provide a theoretical reference for setting the minimum distance between a tunnel and interchange exit.

1. Introduction

With the development of mountainous highways in China, limited by topography and geological conditions, the spacing between tunnels and front main line interchange exits is generally decreasing. Studies have shown that traffic accidents with highway tunnel-interchange sections account for approximately 30% of the total [1]. Tunnel-interchange sections contain diversion areas, so there are many lanes changing, which can be discretionary or mandatory [2]. Mandatory lane changes are mainly manifested in diversion areas from the tunnel to the interchange [3]. Since lane change is not allowed in a highway tunnel, drivers who want to leave the main line must change lanes from the inner lane to the outer lane and drive into the ramp within a certain distance. This process of purposeful lane change is called mandatory lane changing of an off-ramp vehicle [4]. Affected by the “white hole effect” of the tunnel exit, the lane-changing behavior of small spacing sections of the tunnel to interchange differs from the original diversion area [3, 5]. This process includes the process of “light adaptation,” the process of reading signs, the process of lane change decision-making, and the process of the lane change. When the driving environment is complicated, the driver must deal with the information and consider more factors when changing lanes [6, 7].

Hence, it is necessary to explore the driving behavior influence mechanism in the lane-changing process of small spacing from tunnel to interchange.

Many studies have examined the influencing factors in the process of lane changing in highway diversion areas, but few have addressed mandatory lane-changing behavior in a diversion area of small spacing in tunnel-interchange sections. To explore the driving behavior influence mechanism in the lane-changing process of small spacing from tunnel to interchange, it is important to further explore the lane-changing behavior of the off-ramp vehicles. The mandatory lane-changing duration is an important characteristic of lane-changing behavior, which can be used to study the mechanism of lane changes [8]. The mandatory lane-changing duration is defined as the duration between the moment when the driver finishes reading the advance guide sign and the moment when the lane change ends. The main objective of this study was to analyze influence mechanism of the mandatory lane-changing duration in a diversion area of small spacing in tunnel-interchange sections. For the convenience of subsequent research, we denote the mandatory lane-changing duration as MLCD. The objective of this paper is threefold: (a) built a simulation model on a driving simulation platform according to the real-world scene; (b) study of the characteristic of the survival function of the MLCD through the Kaplan–Meier regression model; (c) investigation of the influencing factors of lane change through the Cox regression model. The contribution of this study is the analysis of the mechanism of the mandatory lane change in a diversion area of small spacing in tunnel-interchange sections from the perspective of survival analysis. This research work provided a theoretical reference for optimizing traffic organization in small spacing sections of highway tunnel-interchange sections and improving highway service levels.

The remainder of this paper is organized as follows. Section 2 provides a literature review, Section 3 describes our experiment, Section 4 discusses the results, Section 5 provides an improving method, and Section 6 presents our conclusions and suggestions for future work.

2. Literature Review

2.1. Characteristics of Lane Change in Highway Diversion Area. Many studies have focused on safety issues associated with mandatory lane-changing behavior in highway diversion areas. Hao et al. [9] proposed a probability density model for the location distribution characteristics of vehicle forced lane changes in highway diversion areas based on the driver's lane-changing intention and the headway of the target lane. Qu et al. [10] took the highway as the research object to evaluate the risk level of traffic accidents in the confluence area and found that the lane change frequency determined the accident risk level. Li et al. [11] used game theory to establish a lane selection behavior model for drivers in highway diversion areas. Lyu et al. [12] used real vehicle tests to collect the vehicle speed, trajectory, and position parameters in the process of lane changes in highway diversion areas to analyze the lane-changing characteristics of different driving groups and found that males generally drive into the inner lane earlier, and experienced drivers enter the deceleration lane as soon as possible. Dou et al. [13] developed a model based on vehicle lane-changing data from Interstate Highway 80 and U.S. Route 101 in the United States to analyze the mandatory lane-changing behavior of drivers. Ali et al. [14] used a parametric accelerated failure time hazard-based duration model to study the minimum gap time between the interacting vehicles during the mandatory lane-changing. Duration is another important characteristic of lane-changing behavior [15–17]. Studies have demonstrated that the duration of a lane change roughly ranges from 0.5 s to 16 s and obeys a normal distribution [18]. It has been shown that many influencing factors might affect lane change duration, such as vehicle types [19], driver characteristics [20, 21], road types [21, 22], traffic density, and interactions with surrounding vehicles [23].

Unlike previous research, this paper considers the influence of upstream tunnels on lane-changing vehicles in diversion areas. The factors that affect the lane-changing behavior of off-ramp vehicles in small spacing sections of tunnel-interchange sections are more complex than those in original road sections. This paper attempts to take the MLCD of an off-ramp vehicle as the breakthrough point and analyzes the influencing factors from the perspective of survival analysis. The reason why we choose this perspective is due to its merit and popularity in mining the mechanism behind the lane-changing behavior data.

2.2. Survival Analysis Application in Transportation Analysis. Survival analysis is a statistical modeling method used to study time data. This method links event results with duration and quantitatively analyzes factors affecting event duration. Over the past decades, it has been widely used in the field of transportation. Li [24] used an accelerated failure time hazard-based model to develop estimation and prediction models and considered unobserved heterogeneity, time-varying covariates, and the relationship between consecutive traffic incident duration stages. Gao et al. [25] used survival analysis to establish a model to resolve the issue of censored data of the waiting time of e-cyclists at an intersection and used the Kaplan–Meier estimator to examine the significance of the difference in red-light running between regular and delivery-service e-cyclists. Haque and Washington [26] collected the time data of distracted driving by an indoor simulation test and analyzed its influencing factors. Zheng et al. [27] proposed a quantitative approach to evaluate the effects of mixed traffic flow, such as the duration of traffic congestion [28, 29], duration of traffic events [30], and time of pedestrians crossing the street [31, 32], on bus running times (except bus dwell times) near bus-stop areas based on linear regression and survival analysis theory.

The duration of vehicles from the starting point to the ending point of a lane change can be understood as "survival time" [33], and survival analysis methods can quantitatively analyze various factors affecting it. Li et al. [33] analyzed lane-changing duration from the perspective of survival analysis. Using the HighD dataset of natural driving trajectory, the lane-changing duration survival function characteristics and influencing factors were studied. Nan et al. [34] proposed a survival analysis approach to model e-bikers' lane-transgressing behavior, including the Kaplan–Meier curve and the Cox proportional hazards model. Liu et al. [35] used a driving simulator to study lane-changing behaviors on the highway.

Although existing research has achieved certain progress, there is still a paucity of research on the mandatary lane-changing behavior in a diversion area so far, let alone using the survival analysis methods since most efforts in lane change have been devoted to a discretionary lane change or the decision-making process and the impact of lane change. Furthermore, a systematic comparative univariate and regression analysis of the mandatory lane-changing behavior in a diversion area of small spacing in tunnel-interchange sections is still lacking. These questions would inevitably hinder us from having a deeper analysis of optimizing traffic organization in small spacing sections of highway tunnel-interchange sections. To address these needs, we intend to use the survival analysis method to study the MLCD of off-ramp vehicles in the small spacing section of a highway tunnel-interchange section. The survival analysis method was adopted to study the distribution characteristics of the time-to-line crossing in lane changing, and the Cox proportional hazards model was established through nonparametric survival analysis.

3. Methods

3.1. Participants. We selected 42 participants for a simulation experiment according to the method of calculating the minimum sample size in mathematical statistics [36]. The sexes and ages of participants were controlled according to the characteristics of Chinese motor vehicle drivers, to obtain 22 males and 20 females with an average age of 27 years (range 22–38 years). All participants held a Chinese driver's license, had driven for 1–10 years, and had mountain driving experience. Corrected or uncorrected visual acuity was above 5.0. There was no color blindness or weakness, no physical or psychological diseases and the subjects were in good physical condition. To explain briefly, the homogeneous sample of subjects selected to minimize any bias attributable to sample heterogeneity, we calculate the required sample size, based on expected variance, target confidence level, and margin of error. The method of measuring the sample size is shown by the following:

$$n = \left(\frac{Z\sigma}{d}\right)^2. \tag{1}$$

As written in (1), the required sample number (n) is calculated by the standard normal distribution (Z), the variance (σ) and the maximum error (d). Typically, a 10% level of significance is chosen to reflect a 90% confidence regarding the unknown parameter. So the Z is 1.96, in this paper, the Z is 1.96 and the σ is 0.5; the d is 10%. So the required sample size in this paper is 42.

3.2. Test Apparatus. To study the characteristics of MLCD under the influence of different factors in small spacing sections of highway tunnel-interchange sections, we used UC-win/Road simulation software and the PXN-V3 Pro driving operating system to build a test simulation scene. Although there is some difference between an indoor simulation test and the real world, it effectively overcomes the problems of high risk, difficult control variables, and large test error [37, 38]. The system simulates the translation motion of a vehicle in three-dimensional space according to a real-time driving state and realizes motion simulation with six degrees of freedom. A simulator can create almost any driving scene, including terrain input, road definition, and traffic flow generation. It is convenient to set the parameters of influencing factors to control a single variable, and data of vehicle speed, trajectory, and motion time can be recorded at a data acquisition frequency of 60 Hz.

3.3. Test Design. Off-ramp vehicles on the left lane usually have a mandatory lane-changing behavior, which has high research value. The tunnel-interchange small spacing section of Yuxiang Highway in the western mountainous areas of China was taken as a prototype to build the simulation test section. According to aerial photography records and statistical analysis, the proportion of bridge tunnels in the highway is as high as 70%, which consists mainly of medium and long tunnels. The lengths of small spacing sections of tunnel-interchange sections are concentrated in the range of 400 m–600 m, which is far less than the 1000 m specified in the criteria. The "Design specification for highway alignment" (JTG D20-2017) [39] generally stipulates that the distance between the tunnel exit and the starting point of the deceleration lane shall not be less than 1000 m. Therefore, the influence of the distance of the spacing section is mainly considered in the establishment of the model in this paper. Traffic of small, medium, and heavy vehicles accounted for 68%, 14%, and 18%, respectively. The simulation test section set up in this test was the most common one-way two-lane mountain highway tunnel, with a speed limit of 80 km/h, which was lifted outside the tunnel. Traffic composition was set to mixed flow, with small, medium, and heavy vehicles in a 7 : 1 : 2 ratio (lane changes were not allowed, and all heavy vehicles were set to the right lane). The length of the parallel deceleration lane was set to 150 m according to "Guidelines for the design of highway grade-separated intersections" (JTG/T D21-2014) [40]. As shown in Figure 1, a solid line was set at 100 m outside the tunnel outlet, and mainline was set within 150 m of the deceleration lane without lane change.

To simplify the test model and highlight the main influencing factors, we selected typical influencing variables from the aspects of vehicle, road, and traffic conditions, without considering drivers and weather factors. Vehicle variables focused on vehicle types; road variables on the distance of small spacing sections, tunnel types, and ramp types; and traffic condition variables on the road service level and whether to set an exit advance guide sign in the tunnel.

To control the test variables, the main lines were straight sections, including preparation sections and four test sections, and each section was connected by a ramp. The preparation section familiarized participants with the operation,

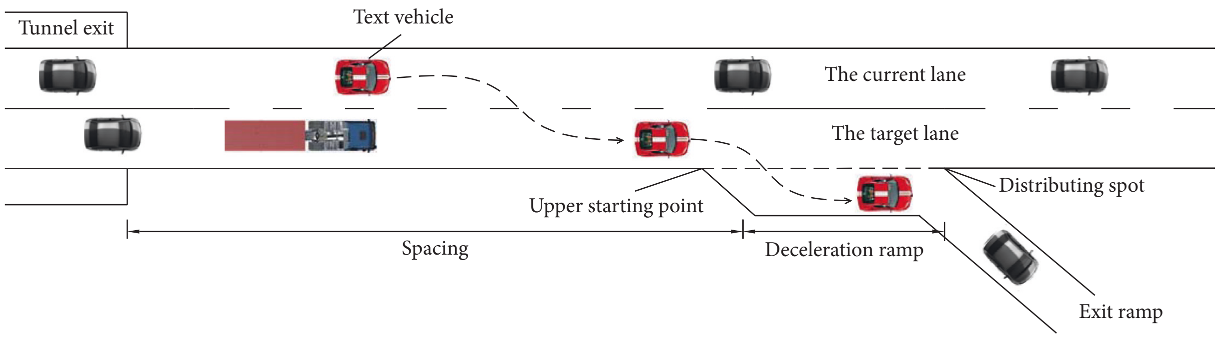

Figure 1: Simplified lane change model of small spacing section.

Figure 2: Test-driving scene.

(a) (b)

Figure 3: Validation of model accuracy (a) the real scene and (b) the simulation scene.

enabling them to adapt to the simulation environment and reduce the test error. The distance between the tunnel exit and the upper starting point of the deceleration lane was the main setting variable in the four test sections, and other influencing variables were randomly combined. To study a driver's mandatory lane-changing behavior, the initial lane of the test vehicle was set in the left lane. When a driver with a demand for driving out of the main line exited the tunnel in the left lane, the mandatory lane-changing behavior occurred. The test-driving scene is shown in Figure 2. Each participant carried out four parallel tests on test sections of different distances, for a total of 168 sample data points.

3.4. Validation of Model Accuracy. Although the simulation scene built based on UC-Win/Road is similar to the real scene, there is a certain distortion. Therefore, it is necessary to verify the accuracy of the simulated driving scene. In this paper, stimulation of subjectively equal speed (SSES) was used to verify. SSES refers to the physical speed of the simulation scene when the driver's perception speed of the simulation scene is equal to that of the real scene [41]. Both the real scene and the simulation scene are highway tunnel sections, as shown in Figure 3. The driving speed in the real vehicle test (Figure 3(a)) was 82 km/h. The simulated driving speed was 82 ± 20 km/h with a minimum interval of 2.5 km/h. The limit method was used to assess the accuracy between these two models. As shown in Table 1, the result was 79.5 km/h with a model error of 3.05% (smaller than the error range of 5%), According to the results of single sample T-tests $p = 0.13$, there was no significant difference between the real scene and the simulation scene.

3.5. Survival Analysis Framework of MLCD. A survival analysis model generally combines the result of an event with its time of occurrence. It is usually used to explore the correlation between event duration and influencing factors [42].

Table 1: Validation of model accuracy.

Driving scene	Speed (km/h)	Error (%)	Single sample statistics		T-tests ($\alpha = 0.05$)		
			Simple size	Standard error	Sig.	95% confidence interval	
						Lower	Upper
Real driving scene Simulation driving scene	82 79.5	3.05	20	2.67	0.13	77.37	84.21

3.5.1. Elements of Survival Analysis. Following the concept of survival analysis, the five elements of the MLCD of off-ramp vehicle survival analysis are defined as follows:

(1) Event. The starting point of the event is the moment when the vehicle begins to turn and changes lanes; the ending point is the time when the lane changes to the target lane and returns to the positive direction.

(2) Survival Time. The survival time is defined as the MLCD of an off-ramp vehicle, from the moment when it begins to turn and changes lanes to the moment when it changes to the target lane and returns to the positive direction. The time difference between the two moments is the MLCD of the vehicle.

(3) Event Result. The event result σ indicates whether the mandatory lane changing of an off-ramp vehicle is completed. When the vehicle completes a lane change within the specified area, $\sigma = 1$, and when the vehicle completes the lane change outside the specified area or does not complete it, then $\sigma = 0$, that is exist censored value, which means "invalid lane-changing." This is a situation where a driver changes lanes at a solid line or misses a ramp.

(4) Cumulative Survival Function S (t). The cumulative survival function of the MLCD represents the probability distribution of the off-ramp vehicle lane change to time t, which in essence is a cumulative survival probability,

$$\begin{aligned} S(t) &= P(T > t) \\ &= \int_{1}^{\infty} f(x)\mathrm{d}x \\ &= 1 - F(t), \end{aligned} \tag{2}$$

where T is the duration, $f(x)$ is the probability density of time x, and $F(t)$ is the distribution function.

A steep survival curve indicates a low survival probability, and a flat curve indicates a high survival probability.

(5) Cumulative Hazard Function H (t). The hazard function represents the probability of the end of the forced lane change in unit time Δt under the condition of t, which is essentially the conditional survival probability,

$$\begin{aligned} H(t) &= \lim_{\Delta t \longrightarrow 0} \frac{P(t \le T < t + \Delta t \mid T \ge t)}{\Delta t} \\ &= \frac{f(t)}{S(t)} \\ &= -\frac{\mathrm{d}}{\mathrm{d}t} S(t). \end{aligned} \tag{3}$$

The cumulative hazard function curve is obtained by integrating the hazard function. The higher its position, the higher the probability of the end of the forced lane change in the next unit of time.

3.5.2. Kaplan–Meier Regression Model. Compared with the parametric model, the nonparametric model does not need to assume the distribution, which can better solve the estimation problem when the data does not obey the specific distribution. Combined with the data in this paper obeying the skewed distribution, the nonparametric survival model is selected [42]. The Kaplan–Meier nonparametric model requires no assumptions on its theoretical distribution. It can directly estimate the survival and risk functions of event duration t, and quantitatively analyze the distribution characteristics of event duration under a single influencing factor. The estimation function of the event duration survival function based on the Kaplan–Meier model is

$$\widehat{S}(t) = \prod_{T_i^c \le t} \frac{n - i}{n - i + 1}, \tag{4}$$

where T^c is the complete sample; T_i^c is the complete sample i representing the duration of the event, and $T_i^c \in T^c$.

S (t) is a nonincreasing function of t, with a value of 1 at the beginning of the lane change ($t = 0$). With the lane change, it gradually decreases and finally tends to 0. The steeper the survival curve is, the faster the survival rate is reduced, i.e., the more forced lane changes of off-ramp vehicles in this period, the flatter the survival curve, the slower the decrease of the survival rate, and the longer the lane change duration.

3.5.3. Cox Regression Model. The Cox regression model is a proportional hazard model that analyzes the influence of covariates on survival time,

$$h(t, x) = h_0(t)\exp(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i), \tag{5}$$

where t is the duration of traffic events, x is a covariate, β is a regression coefficient, h (t, x) is the hazard function, and h_0 (t) is the basic risk function that represents the hazard function inherent in the event duration without other factors. It is often used to quantitatively analyze the intensity and direction of the influence factors, and to obtain the risk function of the change of the event survival state at each moment.

Logarithmic transformation of (4) gives

$$\ln \frac{h(t,x)}{h_0(t)} = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i. \tag{6}$$

When the regression coefficient $\beta_i > 0$, then the independent variable is a risk factor. The greater the value of the regression coefficient β_i, the larger the hazard function, indicating that the instantaneous probability of the mandatory lane change ending at time t is higher. When $\beta_i < 0$, the independent variable is a protective factor that tends to reduce the risk level and prolong the forced lane change time.

4. Results and Discussion

4.1. Data Description and Variable Definitions. A total of 168 groups of sample data were acquired in this experiment, including 154 valid lane changes and 14 invalid lane changes, as shown in Table 2. The overall distribution of MLCD data is shown in Figure 4, with an average of 5.993 s, median of 5.900 s, and standard deviation of 2.148 s. It can be found that the median was slightly lower than the average, indicating that the MLCD of most vehicles was lower than the median, and the excessive lane-changing duration of some vehicles increased the overall average. The proportions less than 4 s and less than 9 s were 17.2% and 7.1%, respectively, and 75% of the data was distributed in the range of 4–9 s. A normal distribution test was conducted on the channel switching duration data. The skewness coefficient was 0.026 and the kurtosis coefficient was 0.832, showing a relatively flat positive skewness distribution.

According to the rule of the survival analysis model for the influencing factors, the typical influencing factors X_1, X_2, X_3, X_4, X_5, and X_6 were selected from the vehicle, road, and traffic conditions, as shown in Table 3.

Table 2: Statistics of lane-changing data.

Spacing (m)	Valid lane changing	Invalid lane changing	Total
300	33	9	42
400	37	5	42
500	42	0	42
600	42	0	42
Total	154	14	168

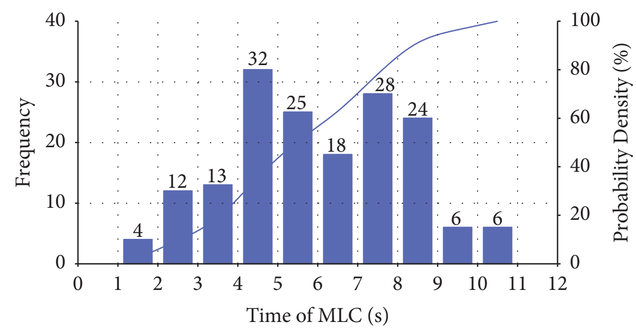

Figure 4: Total distribution of MLCD.

4.2. Analysis of Lane Change Trajectory and Feature Points. To explore the lane-changing time mechanism in more complex situations, the trajectory of the test vehicle in the lane-changing process was extracted and analyzed, as shown in Figure 5, taking the distance between the test vehicle and the left lane line as the main reference index. The average time interval is the time from the trajectory feature points to the upper starting point of the deceleration lane. The lane-changing feature points include the starting, crossing, and ending points.

The lane-changing trajectory of the test vehicle under different spacings is shown in Figure 6, and the average time interval of the lane-changing feature points is shown in Figure 7. Figure 6 shows that the curve of 300 m is obviously steep compared with the curves of 500 m and 600 m. The starting point is earlier, and the ending point is after the upper starting point of the deceleration lane. We found that the spacing is too short, and the driver needs to complete the lane-changing behavior in a short time after reading the guidance signs. According to Figure 7, the average time interval of the lane-changing feature points increases with the spacing of the tunnel-interchange section. When the spacing increases to a certain range, the average time interval of the lane-changing feature points tends to be stable. With the spacing of 300 m and 400 m, the average time interval of some lane-changing feature points is negative, indicating that the lane change feature point is located behind the upper starting point of the deceleration lane. For example, at a spacing of 300 m, the average time interval of the crossing point and ending points were −1.029 s and −3.088 s, respectively. The conversion at the speed of 60 km/h (the minimum speed limit of highway) was 17.150 m and 51.467 m, respectively. It indicates that the lane-changing feature point was located behind the upper starting point of the deceleration lane. In addition to the mandatory lane-changing behavior from the left lane to the right lane, drivers who want to drive away from the main line must change from the right lane to the deceleration lane before the ramp exit. There is a continuous mandatory lane-changing behavior. However, when the spacing increases to 500 m, the average time interval of lane-changing feature points is greater than zero, indicating that vehicles have a sufficient lane-changing distance.

4.3. Analysis of Duration Distribution Characteristics of Mandatory Lane Change Based on Kaplan–Meier Model. To analyze the key influencing factors of the MLCD of off-ramp vehicles, Kaplan–Meier's nonparametric survival analysis was used to establish their survival and hazard functions, the log-rank test was used to evaluate its dominance hypothesis, and the distribution characteristics of the MLCD under a certain influencing factor were quantitatively analyzed.

4.3.1. Vehicle Factors. The survival and hazard functions of the MLCD of off-ramp vehicles under X_1 are shown in Figure 7.

Figure 8(a) shows that there is no significant difference in the survival curve of the MLCD between small and medium vehicles, and the p value of the log-rank test is 0.35,

Table 3: Influencing factors and variable assignments.

Category	Influencing factors	Variable assignment
Vehicle	Vehicle type (X_1)	X_{10} = small, X_{11} = medium
Road	Distance between tunnel exit and deceleration lane upper starting point (X_2)	$X_{20} = 300$ m, $X_{21} = 400$ m, $X_{22} = 500$ m, $X_{23} = 600$ m
	Tunnel type (X_3)	X_{30} = small & medium, X_{31} = long & extra-long
	Ramp type (X_4)	X_{40} = direct, X_{41} = parallel
Traffic condition	Road service level (X_5)	X_{50} = first service level (550 pcu/h), X_{51} = second service level (1200 pcu/h), X_{52} = third service level (1550 pcu/h)
	Exit advance guide sign in tunnel (X_6)	X_{60} = no setting, X_{61} = setting

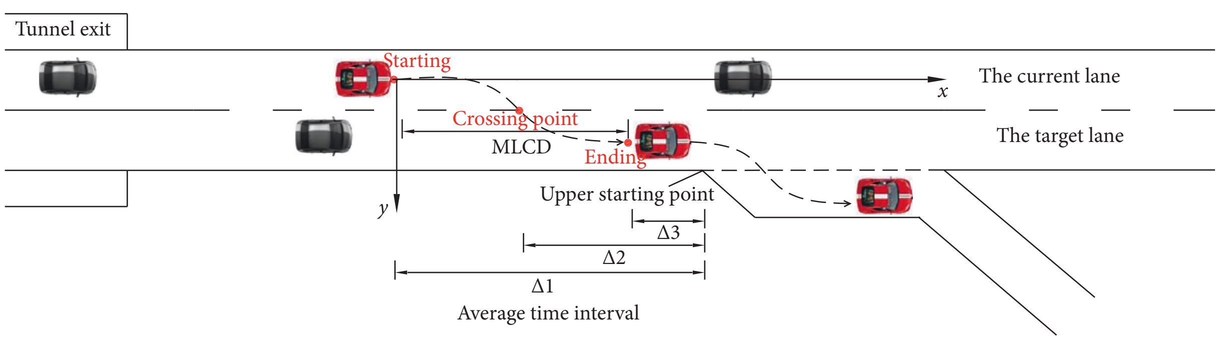

Figure 5: Schematic diagram of mandatory lane-changing trajectory.

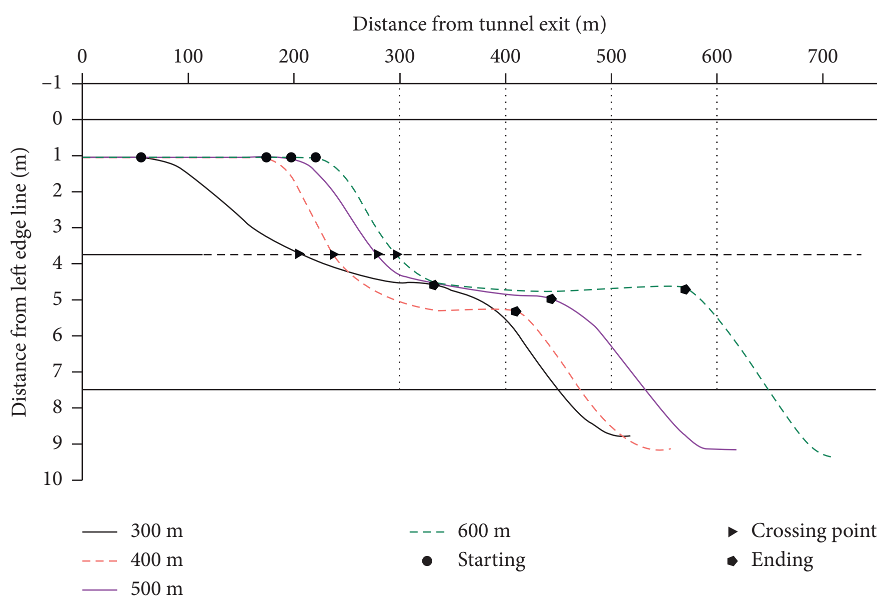

Figure 6: Mandatory lane-changing trajectory of different spacings.

which is greater than 0.05, indicating no significant difference in the influence of small and medium vehicles on the MLCD. This is because the design of small and medium vehicles in the simulation experiment was not obviously different, and the drivers did not feel any significant difference during driving.

4.3.2. Road Factors. The survival and hazard functions of the MLCD of off-ramp vehicles under X_2, X_3, and X_4 are shown in Figure 9. Nonparametric estimation was performed using different spacings as classification factors, and the survival time statistics are shown in Table 4.

It can be seen from $p < 0.05$ of the log-rank test that the spacing between the tunnel and interchange exit significantly affects the MLCD of the off-ramp vehicle. When the spacing is 300 m, the MLCD is the shortest, at 3.802 s, but at 500 m and 600 m, the MLCD is 7.449 s and 6.907 s, respectively. Figure 8(a) shows that within 2 s of the beginning of lane changing, the survival curves coincide and the trend is gentle, indicating that no mandatory lane change occurs within 0–2 s; two seconds later, the survival curve of 300 m is

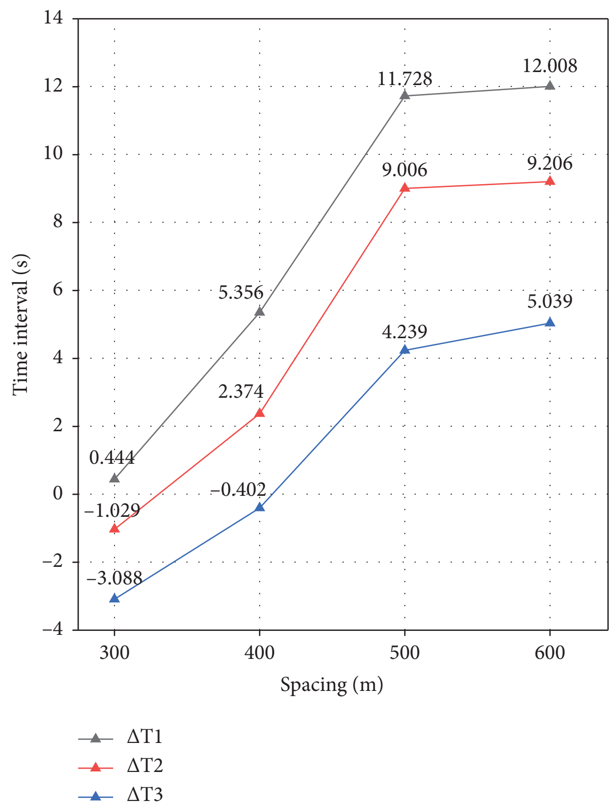

FIGURE 7: The average time interval of lane-changing feature points of different spacings. ΔT_1, ΔT_2, ΔT_3, respectively, are average time interval of starting point to upper starting point, crossing point to upper starting point, and ending point to the upper starting point.

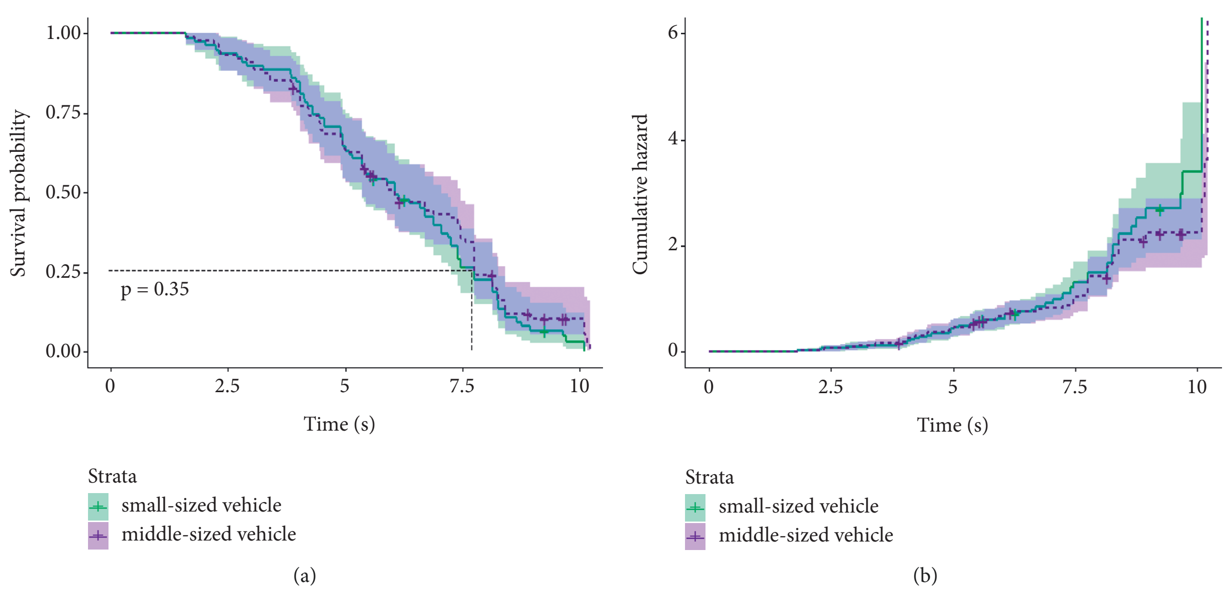

FIGURE 8: Distribution characteristics of MLCD under vehicle factors. (a) Cumulative survival function curve of vehicle types. (b) Cumulative hazard function curve of vehicle types.

steep and the decline rate significantly accelerates. At the same time, differences between spacing groups begin to appear; four seconds later, the survival curves of 500 m and 600 m show a downward trend that lasts a long time. At 300 m and 400 m, a censored value indicates the lane change failure of the spacing. Therefore, the distance of the small spacing section between the tunnel and the deceleration lane should not be less than 500 m, which is consistent with the distance obtained using traffic conflict technology [43, 44], but quite different from the Patrick studies [45]. Currently,

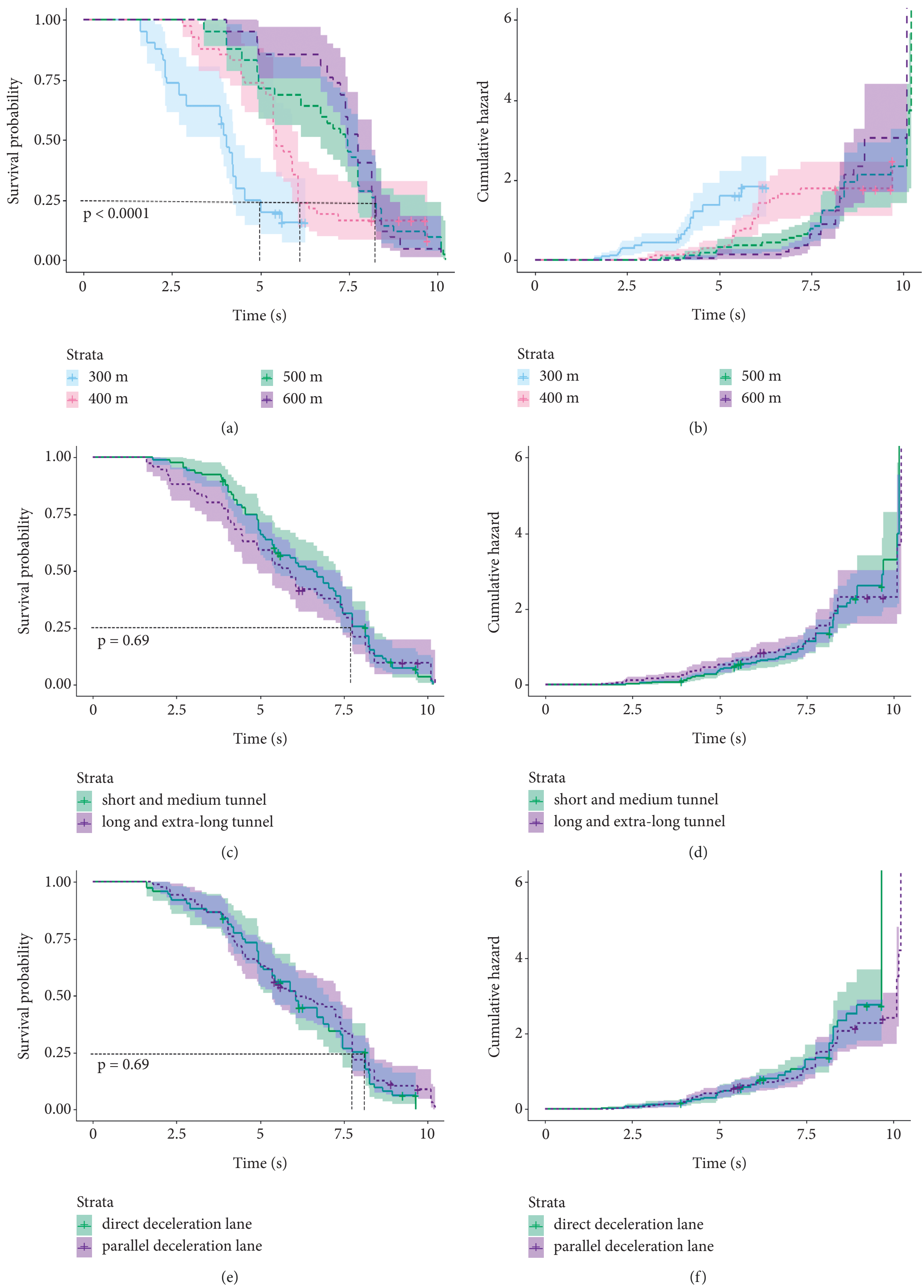

FIGURE 9: Distribution characteristics of MLCD under road factors. (a) Cumulative survival function curve of spacing. (b) Cumulative hazard function curve of spacing. (c) Cumulative survival function curve of tunnel types. (d) Cumulative hazard function curve of tunnel types. (e) Cumulative survival function curve of deceleration types. (f) Cumulative hazard function curve of deceleration types.

Table 4: Statistical results of MLCD under the influence of different spacings.

Spacing (m)	Total cases	Invalid cases	Average Estimate	Average Standard error	Average 95% confidence interval Lower	Average 95% confidence interval Upper	Median Estimate	Median Standard error	Median 95% confidence interval Lower	Median 95% confidence interval Upper	Log-ran test
300	42	8	3.802	0.208	3.395	4.209	3.966	0.123	3.725	4.207	0.000*
400	42	6	5.815	0.286	5.254	6.375	5.450	0.206	5.046	5.854	—
500	42	0	7.449	0.214	7.030	7.868	7.750	0.139	7.477	8.023	—
600	42	0	6.907	0.300	6.320	7.494	7.400	0.366	6.683	8.117	—

Log-rank test is used to determine whether there are significant differences between survival functions. $p < 0.05$ indicates a significant difference; $p \geq 0.05$ indicates no significant difference.

the off-ramp vehicle has a continuous lane-changing behavior because the distance of the spacing section of the tunnel interchange is too small, and drivers cannot respond to the failure of the lane change, which further verifies the conclusion drawn from the lane-changing trajectory. Figure 9(b) shows the cumulative hazard function curve of the MLCD of off-ramp vehicles with different spacings. The hazard function of the lane change time is an increasing function of t. The longer the lane-changing duration, the greater the probability of completing the lane change at the next moment. The risk of "death" (complete mandatory lane changing) of vehicles at the same time increases as spacing decreases.

Figures 9(c) and 9(e) show that the p values of the log-rank test of the tunnel and ramp types are greater than 0.05, indicating no significant difference in the MLCD of the off-ramp vehicle. Since lane changing is prohibited within 100 m outside the exit of a tunnel [40], the driver could safely pass the "white hole effect" stage within 100 m [46], and the tunnel type had little effect on the driver's lane-changing behavior.

4.3.3. Traffic Condition Factors. The survival and hazard functions of the MLCD of off-ramp vehicles under X_5 and X_6 are shown in Figure 10.

The p values of the log-rank test are far less than 0.05, indicating that the road service level and whether to set the exit advance guide signs in the tunnel as a single factor analysis significantly affect the MLCD of off-ramp vehicles. The survival curve of the third service level is obviously above those of the other two service levels, while the hazard function curve is obviously below them. The 75% quantile is 9.20 s, indicating that the MLCD of 75% of vehicles under the influence of the third service level reaches 9.20 s. Because the traffic volume is too large and the lane change gap of the off-ramp vehicle is small, drivers change lanes by reducing speed or waiting to find a lane change opportunity. It can be seen in Figure 10(c) that when exit advance guide signs are set in the tunnel, the MLCD of the off-ramp vehicle is significantly lower, and the starting points of lane changing are earlier. This is because the driver has certain psychological expectations after receiving the warning information in the tunnel, and prepares for lane changing as soon as possible after driving out of it, which is similar to the conclusion of Shang [47].

4.4. Multivariate Analysis Based on Cox Regression Model. Many factors affect the MLCD of off-ramp vehicles. If the regression equation ignores some independent variables that have a significant influence on the dependent variable, the established regression prediction model is too idealized. However, when there are too many variables, the accuracy of the regression equation will be affected if the prediction model contains variables that have little influence on the dependent variable; hence, these should be eliminated. The Kaplan–Meier regression model lacks the control of other parameters. It is necessary to assume that other influencing factors are completely random and have no influence, which only applies to the analysis of the influence of a single variable. Therefore, the Kaplan–Meier model can be used to eliminate variables that are not obvious. After analyzing, one by one, the influence of six factors on the MLCD in the Kaplan–Meier model, it is found that X_2, X_5, and X_6 have significant influence, while X_1, X_3, and X_4 have no significant influence, so the Cox regression model is used to eliminate the influence in advance. The Cox semiparametric survival model is established by selecting X_2, X_5, and X_6 as covariates. The parameter estimation results of the multi-classification variables are shown in Table 5.

β is the regression coefficient, with standard error SE; sig is used to test the significance level of parameter estimation of each covariate, where a value less than 0.05 indicates that a covariate is significant; and exp (β) characterizes the change of the event duration risk rate for each unit increase in the covariate.

According to the semiparametric estimation results, the Cox proportional hazard function of an off-ramp vehicle completing a mandatory lane change at a time t after the start of lane changing is:

$$\begin{aligned}\ln\frac{h(t,X)}{h_0(t)} &= \beta_1 X_{21} + \beta_2 X_{22} + \beta_3 X_{23} + \beta_4 X_{51} + \beta_5 X_{52} + \beta_6 X_{62} \\ &= -1.738X_{21} - 2.360X_{22} - 2.596X_{23} + 0.689X_{51} \\ &\quad + 1.556X_{52} + 0.588X_{62}.\end{aligned} \tag{7}$$

According to the results of the Cox regression model, the regression coefficients of the multi-classification variable's different spacings are all negative, indicating that when spacing of 300 m is used as a comparison, the MLCD will be longer when the spacing increases by 100 m. Taking X_{21} as an example, the regression coefficient is −1.738 and the relative

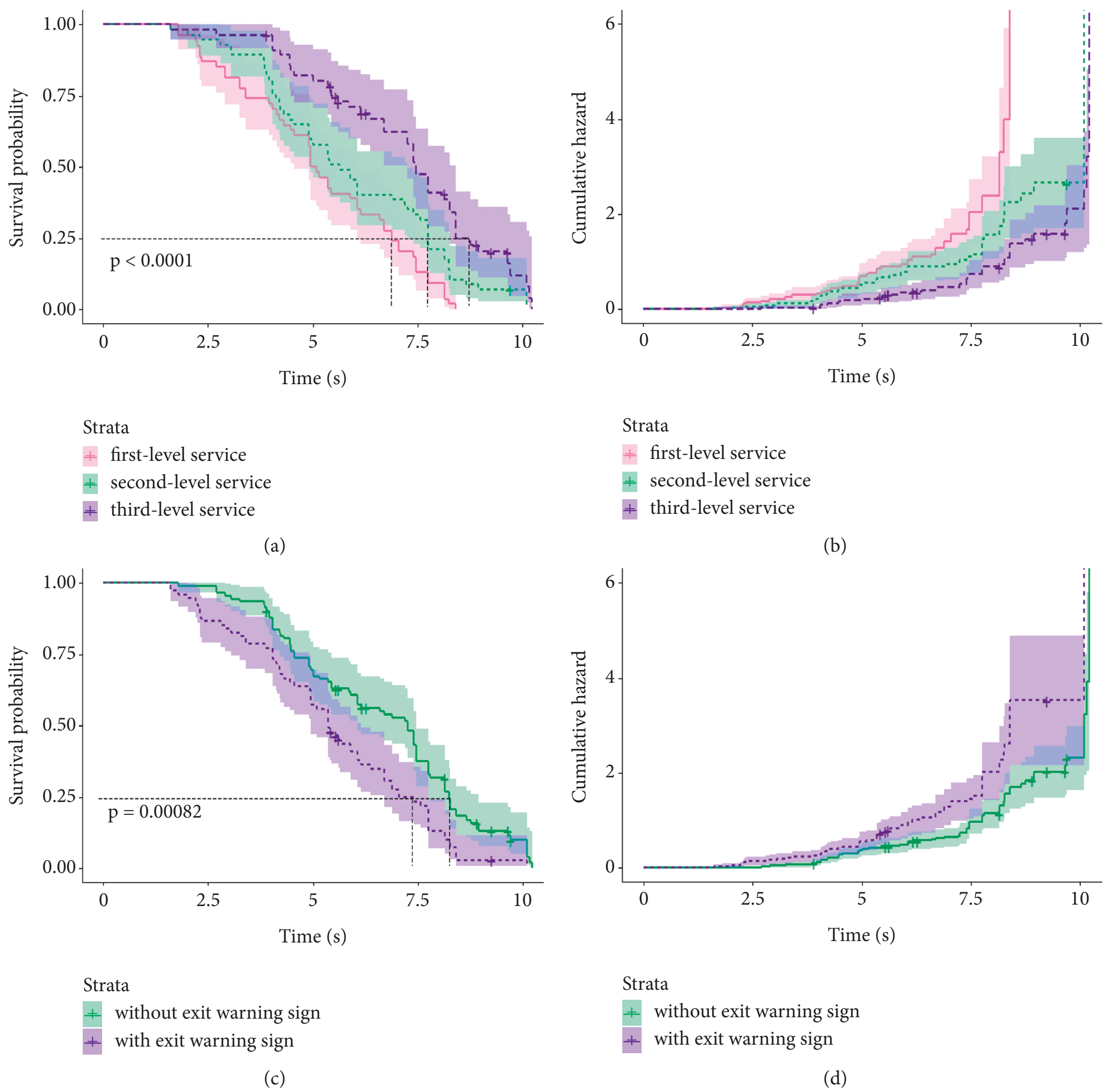

Figure 10: Distribution characteristics of MLCD under traffic conditions. (a) Cumulative survival function curve of road service level. (b)Cumulative hazard function curve of road service level. (c) Cumulative survival function curve of setting exit advance guide signs. (d)Cumulative hazard function curve of setting exit advance guide signs.

Table 5: Estimation results of Cox model parameters.

Covariate	β	SE	Wald	Sig.	Exp (β)	95% confidence interval	
						Lower	Upper
X_{21}	−1.738	0.274	40.133	0.000	0.176	0.103	0.301
X_{22}	−2.360	0.299	62.023	0.001	0.094	0.053	0.170
X_{23}	−2.096	0.311	69.683	0.294	0.125	0.041	0.137
X_{51}	0.689	0.201	11.727	0.000	1.992	0.339	0.745
X_{52}	1.556	0.231	45.394	0.030	4.739	0.134	0.332
X_{61}	0.588	0.170	11.951	0.001	1.800	1.290	2.511

risk is 0.176, indicating that when the spacing decreases from 400 m to 300 m, the risk rate at the end of the lane change increases 5.68 times (the reciprocal of 0.176). When the distance increases to 600 m, the change of the risk rate tends to be stable. Due to small spacing, the lane-changing distance of the off-ramp vehicle is short, as is the MLCD, so the risk of lane changing is large, and continuous mandatory lane changes even occur. When the spacing increases, an off-ramp vehicle has sufficient lane-changing distance, and the lane-changing time is long. The regression coefficients of the multi-class variable X_5 are all positive, indicating that with the decrease in the road service level, off-ramp vehicles are greatly affected by surrounding vehicles when executing a mandatory lane change. The greater the traffic volume, the longer the lane change time, and the greater the risk of the lane change. The risk rate of a lane change in the second service level is 1.92 times that of the first service level, while the influence of traffic volume is more obvious under the third service level, and the risk rate increases 4.73 times. The regression coefficient of X_6 is positive, and the MLCD is shortened. This shows that setting the exit warning signs in the tunnel has a significant predictive effect on the driver of an off-ramp vehicle. After receiving the road information in the tunnel, drivers have certain psychological expectations and complete the lane-changing preparation in advance.

5. Improving Method

Combined with the analysis results of lane-changing characteristics of a small spacing section of a highway tunnel-interchange section, relevant suggestions for improving the operation safety of this section were put forward. Although this paper selects the simulation model of the Yuxiang Highway in the western mountainous areas of China, it has the same theoretical reference value for the road alignment design, safety facility design, and traffic organization design of similar tunnels to small spacing sections.

(1) It is suggested that the distance between the tunnel and the upper starting point of the deceleration lane should not be less than 500 m. (2) When the distance is less than 500 m, it is recommended to set the upper starting point of the deceleration lane inside the tunnel. A deceleration lane and a lane-changing area are set inside the tunnel so that the off-ramp vehicle completes the lane change before leaving the tunnel. (3) Set the separated exit advance guide sign at the tunnel exit or before the tunnel entrance, and give the driver some psychological expectations [47]. (4) Shading sheds can be set outside the tunnel exit to reduce the influence of “light adaptation” on lane-changing behavior.

6. Conclusion

In order to study the behavior of mandatory lane-changing in a small spacing section of tunnel to interchange of the mountainous highway. We took the small spacing section of a highway tunnel-interchange section as the research object and conducted a survival analysis to establish the regression model of the MLCD of off-ramp vehicles. A nonparametric method was introduced to estimate the overall lane change time distribution in the dataset. It was found that 75% of the data was distributed in 4–9 s, and the lane change time in small spacing sections was longer than that in general sections [33]. We analyzed typical influencing factors selected from the aspects of vehicles, roads, and traffic conditions, including spacing sections of the tunnel-interchange section, vehicle types, tunnel types, ramp types, road service levels, and whether to set exit advance guide signs in a tunnel. The log-rank test showed that the spacing sections of the tunnel-interchange section, road service levels, and whether to set exit advance guide signs in the tunnel had significant effects on the MLCD of off-ramp vehicles, while vehicle, tunnel, and ramp types had no significant effects. When the distance of a small spacing section was less than 500 m, off-ramp vehicles had continuous mandatory lane-changing behavior, and when the distance decreased from 400 m to 300 m, the lane-changing risk rate increased by 5.68 times. The estimation results of the survival curve in Figure 8(a) provided the 75% quantile of the MLCD of off-ramp vehicles with different spacings, which provided a theoretical reference for the setting of the minimum spacing between a tunnel and interchange. A censored value existed when the spacing was less than 500 m, suggesting that the spacing should not be less than 500 m. The conclusion was similar to those of other studies [43, 44], but quite different from the JTG D20-2017 criteria [39]. Improving methods for the road alignment design, safety facility design, and traffic organization design of similar tunnels to small spacing sections are proposed according to lane-changing characteristics of off-ramp vehicles. The main limitation of the paper lies in only considering lane-changing behavior in the case of a two-lane single-hole tunnel from tunnel to interchange. In future research, we will consider the influence of three-lane road types. In addition, the influencing factors of the MLCD selected in this paper were not comprehensive enough, and some simplifications were made in the construction of the research scene. We did not consider influencing factors such as driver factors, tunnel lighting, the orientation of the tunnel, and differences in weather conditions between the real world and the driving simulator. We would collect crash statistics and floating car data to analyze the characteristics of MLCD at smaller distances between tunnels and interchanges. These can be considered in future work.

Data Availability

Data used in this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest.

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