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Research Article

A Study on Correlation of Traffic Accident Tendency with Driver Characters Using In-Depth Traffic Accident Data

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Traffic accidents are often related to the driver's driving behavior, which is mainly decided by his or her characters. In order to explore the correlation of traffic accident risk with driver characters, the age, driving experience, and driving style were statistically analyzed based on the China In-Depth Accident Study (CIDAS) database. Taking the number of casualties in the accident as evaluation indicators, the grey cluster analysis was used to classify the drivers into four accident risk ranks: low, medium to low, medium to high, and high. The results show that drivers aged 18–30 years are more likely to induce accidents; drivers with 6–10 years of driving experience have the highest risk to accidents, followed by drivers with 4-5 years of driving experience; and the driving style is also highly correlated with accident risk tendency.

1. Introduction

In China, especially in urban roads, due to mixed traffic flows, the traffic situation is more complicated. Although the accident rate is decreasing year by year, the number of casualties is still high every year [1]. For example, it is reported 0.9 per cent year-on-year decrease for 2018 in China, but there were still 166,906 traffic accidents in cars, which killed 46,161 people and injured 169,046 people. In addition, according to the reports of traffic accidents, nearly 90% of accidents are caused by human factors, and the human becomes one of the most unstable factors in causing traffic safety problems [2]. Traffic accidents are often related to the driver's driving behavior, which is mainly decided by his or her characters, such as the age, driving experience, and driving style. Drivers' willingness to reflect the driving style characteristics is based on their own driving ability, danger, and emergency handling attitude [3, 4]. It is particularly urgent to study the correlation of traffic accident risk tendency with driver characters.

Accident Tendency Theory is one of the ancient and most widely known accident causation theories, which holds that accidents are indeed related to human personality [5]. In addition, from the statistical point of view, a certain type of driver would show more likely to be accident-prone than other drivers under the same driving environment conditions, which can be called the driver's accident tendency. In other words, accident propensity refers to individuals who have the characteristics of accident-prone among drivers [6].

The Grey System Theory was founded in 1982 by the Chinese scholar Professor Deng Julong. It is a systematic subject with the uncertainty system, which is mainly used to study the "small sample uncertainty problem" and describes the versatile factors that are difficult to describe quantitatively [7, 8]. The generation and development of known information is used to extract valuable information and achieve a correct description of the system's operational behavior, evolutionary rules, and effective monitoring [9]. The problem of traffic accident risk with driver characters is not only complicated but also changes with time and environment. It can be summarized as follows: the system factors are not completely clear, the relationship between factors is not completely clear, the system structure is not fully known, and the principle of the system is not

completely clear, that is to say, the system is an "information incomplete" system. Therefore, the system consisting of people and vehicles is a typical grey system, which is suitable for the grey system theory [10].

Exploring the correlation of traffic accident risk with driver characters, such as the age, driving experience, and driving style, would be an effective way to improve the traffic safety [11]. Based on the statistics of the actual traffic accident cases occurred from 2014 to 2016 in the CIDAS database, this paper analyzes the characters of drivers involved in these accidents, and the grey cluster analysis was used to classify the drivers into four accident risk ranks. This study would provide a theoretical basis for improving the domestic traffic design and standardizing the driving behavior of drivers.

2. Data and Methods

2.1. Data. The China In-Depth Accident Study (CIDAS) project was launched on July 15, 2011, by China Automotive Technology Research Center and several well-known automobile enterprises. It aims to provide basic data support and technical services for the automobile industry through in-depth investigation, analysis, and research on road traffic crashes in China [12].

356 crash cases are selected from the road vehicle accidents of the CIDAS project from 2014 to 2016 based on the following sampling criteria: (1) passenger car involvement, (2) detailed records of driver characters, (3) detailed injury records, (4) clear causation of the accident, and (5) age of the drivers ranging between 18 and 60 years.

2.2. Methods. A grey cluster evaluation model is established to classify the drivers' accident risk rank, and the main steps are as follows:

(1) Giving the cluster whitening number: select n clustering objects, get m clustering indicators, and construct an $n \times m$ matrix.

(2) Inputting the cluster whitening number into the computer, entering the grey clustering analysis and evaluation algorithm, including the clustering whitening number to be averaged and dimensionless; determining the grey class where each clustering index value belongs to each clustering object; using the valuation method or interpolation method to obtain the whitening weight function value of each grey class; calibrating the clustering weight grey number matrix; and constructing the clustering matrix.

(3) Performing grey evaluation based on the result of step (2).

2.2.1. Definition of Grey Cluster Objects and Indicators. The numbers of minor injuries, serious injuries, and deaths in the accident are selected as the evaluation indicators, and

then the evaluation index matrix is constructed according to the following equation:

$$X_{m \times n} = \begin{bmatrix} 9 & 4 & 5 \\ 10 & 4 & 0 \\ 4 & 2 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 0 \end{bmatrix}, \tag{1}$$

where m represents the number of the evaluation object, $m \in \{1, 2, 3, \cdots, 47\}$; n is the evaluation index, $n \in \{1, 2, 3\}$; and $n = 1, 2, 3$ represents the number of minor injuries, serious injuries, and deaths in the accident, respectively. The range method is used to measure the indicators without dimension, shown as equation (2):

$$X_{mn} = \frac{x'_{mn} - x_{\min}}{x_{\max} - x_{\min}}, \tag{2}$$

where x'_{mn} is the elements in the matrix and $x_{\min}$ and $x_{\max}$ are the minimum and the maximum element in the matrix, respectively. The evaluation matrix after dimensionless processing is shown in the following equation:

$$X_{m \times n} = \begin{bmatrix} 0.9 & 0.4 & 0.5 \\ 1.0 & 0.4 & 0 \\ 0.4 & 0.2 & 0 \\ \vdots & \vdots & \vdots \\ 0.1 & 0 & 0 \end{bmatrix}. \tag{3}$$

2.2.2. Determining of Ash and Whitening Values. The driver accident risk rank is classified into four levels: low, medium to low, medium to high, and high. It is represented by the grey class $k = 1, 2, 3,$ and 4, respectively, and then the evaluation matrix after dimensionless treatment is used to perform the cumulative frequency analysis [13, 14]. The whitening values of the four levels of the driver's risk tendency are represented by $\lambda_n^1, \lambda_n^2, \lambda_n^3, \lambda_n^4$, which are the relative values of the cumulative frequencies of the curves of 15%, 40%, 60%, and 85%, respectively. The matrix of λ is described in the following equation:

$$\lambda = \left(\lambda_n^1, \lambda_n^2, \lambda_n^3, \lambda_n^4\right) = \begin{bmatrix} 0.1 & 0.1 & 0.3 & 0.4 \\ 0 & 0 & 0.1 & 0.3 \\ 0 & 0 & 0 & 0.2 \end{bmatrix}. \tag{4}$$

2.2.3. Construction of the Grey Class Whitening Weight Function. The segmentation function can be used to construct the whitening weight function of the driver's risk tendency of inducing an accident [15–17]. The symbol f_n^k indicates the whitening weight function of the nth clustering evaluation index, which belongs to subclass K. The whitening weight function of the indicator corresponding to minor injury, severely injury, and death is f_1^k, f_2^k, and f_3^k, respectively. Taking the minor injury indicator f_1^k for

example, the whitening weight function of four levels of risk tendency can be obtained from equations (5) to (8)

$$f_1^1 = \begin{cases} 1, & x \in [0, 0.1], \\ 0, & x \in (0.1, 1], \end{cases} \tag{5}$$

$$f_1^2 = \begin{cases} 0, & x \notin [0.1, 0.3], \\ \dfrac{0.3 - x}{0.3 - 0.1}, & x \in [0.1, 0.3], \end{cases} \tag{6}$$

$$f_1^3 = \begin{cases} 0, & x \notin [0.1, 0.4], \\ \dfrac{x - 0.1}{0.3 - 0.1}, & x \in [0.1, 0.3], \\ \dfrac{0.4 - x}{0.4 - 0.3}, & x \in (0.3, 0.4], \end{cases} \tag{7}$$

$$f_1^4 = \begin{cases} 0, & x \in [0, 0.3], \\ \dfrac{x - 0.3}{0.4 - 0.3}, & x \in (0.3, 0.4], \\ 1, & x \in (0.4, 1]. \end{cases} \tag{8}$$

Then, the clustering weight will be determined by the following equation:

$$\eta_n^k = \begin{cases} \dfrac{\lambda_n^k}{\sum_{n=1}^{3} \lambda_n^k} \cdot \left(1 - \dfrac{b}{i}\right), & \lambda_j^k \neq 0, \\ \dfrac{1}{i}, & \lambda_j^k = 0, \end{cases} \tag{9}$$

where η_n^k and λ_n^k are the clustering weight and whitening value, respectively, of the nth evaluation index in the kth grey category and b is the number of λ_n^k, which is equal to 0, $i = 3$.

According to equation (9), the grey cluster weight matrix of each evaluation index can be obtained for each subclass. Then, the reanalysis of grey clustering will be performed, the grey cluster evaluation value σ_m^k, which means the cluster evaluation value of the mth evaluation object in the kth grey class can be determined by the following equation:

$$\sigma_m^k = \sum_{n=1}^{3} f_m^k X_m^n \eta_n^k. \tag{10}$$

The cluster evaluation value sequence of the evaluation object m $\sigma_m^k = (\sigma_m^1, \sigma_m^2, \cdots, \sigma_m^k)$ will be used to identify the accident tendency level of m.

3. Results

3.1. Characters of Accident Vehicles Drivers.
Traffic accidents are often related to the driver's driving behavior, which is mainly decided by his or her characters, and age, driving experience, and driving style are the main characters related with the handling performance [18–22].

3.1.1. Age.
The drivers were divided into four age groups: 18 to 30 years old, 31 to 40 years old, 41 to 50 years old, and 51 to 60 years old. Figure 1 shows the age distribution of the drivers in traffic accident vehicles.
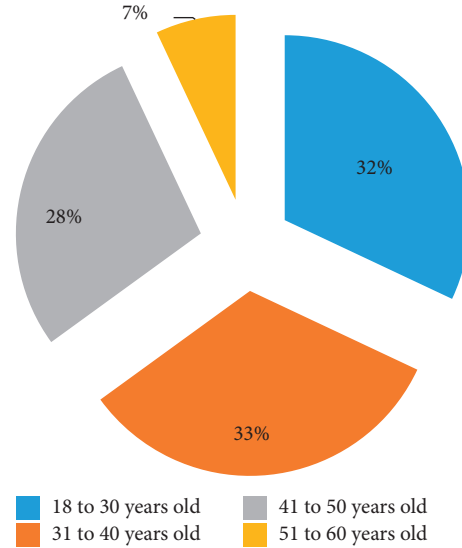

FIGURE 1: Age distribution of the drivers in traffic accident vehicles.

Figure 2 shows the number of casualties caused by different age groups.

Drivers aged 31–40 years account for the maximum number of traffic accidents, while drivers aged 51–60 years have the minimum number of traffic accidents and they also have the lowest casualties. Drivers in the 41–50 age group have the highest number of fatal accidents, followed by drivers in the 51–60 age group. The visual characteristics, response time, speed estimation accuracy, and operation ability of drivers would change with the increase of age to a certain extent [23–25], so age would consequently influence a driver's accident risk tendency.

3.1.2. Driving Experience.
Driving experience is an objective evaluation index related with the driver's driving ability [26–29]. In this study, the drivers were divided into six groups based on their driving experience: 3 years and below, 4 to 5 years, 6 to 10 years, 11 to 15 years, 16 to 20 years, and 20 years and above. Figure 3 shows the distribution of driving experience of drivers in accidents.

It can be seen that the drivers in the 6–10-year driving experience group contribute the most number of accidents, followed by the drivers in the 3-year driving experience group, and the drivers with 20 years or more driving experience account for the lowest number of accidents.

3.1.3. Road Types.
Figure 4 shows the distribution of the road types where the accident occurred. In this study, four kinds of road types are involved: straight, curved road, intersection, and crossroad. The accidents occurred on the straight road account for the highest proportion (44.45%) in the total accidents, followed by intersections and crossroads. If we consider the integration of data at intersections and crossroads, the number of accidents at intersections is more than half of the total number of accidents, which is consistent with other literatures [30–33].
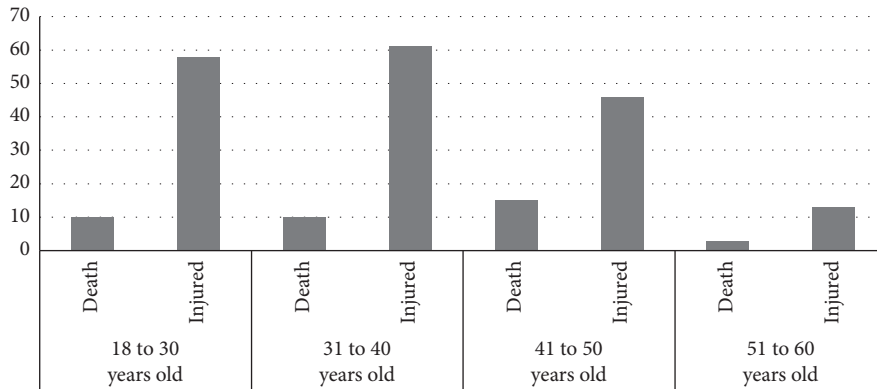
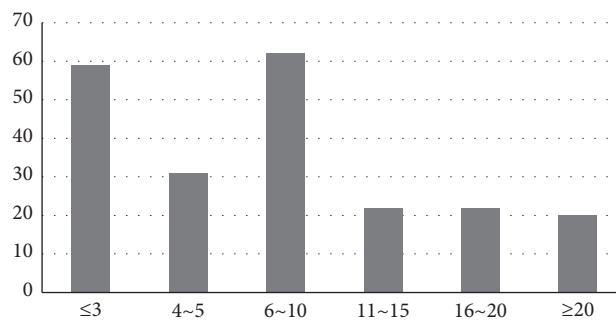FIGURE 2: Casualties caused by drivers of different ages.

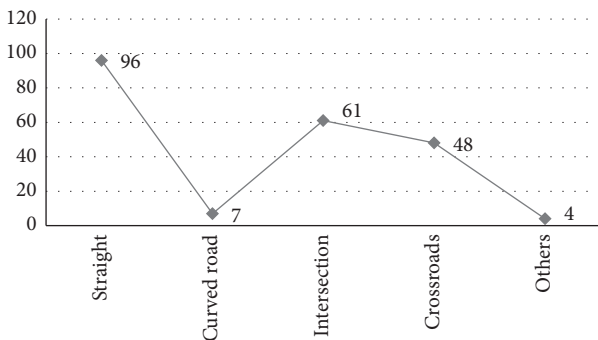FIGURE 3: Distribution of driving experience of drivers in accidents.

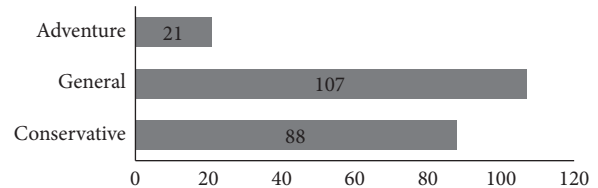FIGURE 4: Distribution of road types in accidents.

FIGURE 5: Distribution of driving styles of drivers in accidents.

3.1.4. Driving Style. Due to the significant deviation of the driver's gender in data samples, the accident cases involved female driver only accounts for 7.5% of the total sample, and the correlation of the driver's driving style with accident risk tendency was analyzed without gender-specific.

Figure 5 shows the distribution of driving styles of the accident vehicle drivers, which were recorded for each accident case in the CIDAS database, but the driving styles were declared by the driver himself. In the CIDAS database, the driving styles include three types that are adventure style, conservative style, and general style [34].

It can be seen from Figure 5, the general style and conservative style should be responsible for most accidents, which were not agreed with common recognition that the adventure style drivers will have higher accident rates [35–38].

3.2. Analysis of Driver's Accident Risk Tendency

3.2.1. Grey Cluster Objects and Indicators. The drivers were divided into 47 classification groups as the object of grey clustering based on their age, driving experience, and driving style. The nonexistent combination and the combination with zero evaluation index were eliminated, as shown in Table 1.

3.2.2. Assessment Value of Drivers' Accident Risk Tendency in Various Character Groups. Table 2 lists the grey clustering assessment value of drivers' accident risk tendency in various character groups, and the groups with high accident risk tendency are given in italic.

TABLE 1: Grouping of driver characteristics.

Number	Driver characters			Evaluation index		
	Age/year	Driving experience/year	Driving style	Slightly injured	Seriously injured	Death toll
1	18 to 30 years old	≤3	Conservative	9	4	5
2	31 to 40 years old	≤3	Conservative	10	4	0
3	41 to 50 years old	≤3	Conservative	4	2	0
	. . .	. . .	. . .	. . .	. . .	. . .
45	51 to 60 years old	11~15	Adventure	0	0	1
46	41 to 50 years old	16~20	Adventure	3	0	0
47	51 to 60 years old	16~20	Adventure	1	0	0

TABLE 2: Grey clustering calculation results of accident tendency of each group with driver characteristics.

Number	Driver characters			Anecdotal tendency
	Age/year	Driving experience/year	Driving style	
1	18 to 30 years old	≤3	Conservative	Medium to high
2	31 to 40 years old	≤3	Conservative	Medium to high
3	41 to 50 years old	≤3	Conservative	Medium to high
4	18 to 30 years old	4~5	Conservative	High
5	31 to 40 years old	4~5	Conservative	Medium to high
6	41 to 50 years old	4~5	Conservative	High
7	18 to 30 years old	6~10	Conservative	Medium to low
8	31 to 40 years old	6~10	Conservative	Medium to low
9	41 to 50 years old	6~10	Conservative	High
10	31 to 40 years old	11~15	Conservative	Medium to high
11	41 to 50 years old	11~15	Conservative	Medium to low
12	51 to 60 years old	11~15	Conservative	Low
13	41 to 50 years old	16~20	Conservative	Low
14	51 to 60 years old	16~20	Conservative	Medium to low
15	41 to 50 years old	≥20	Conservative	Medium to low
16	51 to 60 years old	≥20	Conservative	Low
17	18 to 30 years old	≤3	General	High
18	31 to 40 years old	≤3	General	Medium to high
19	41 to 50 years old	≤3	General	Medium to high
20	18 to 30 years old	4~5	General	High
21	31 to 40 years old	4~5	General	Medium to low
22	41 to 50 years old	4~5	General	Medium to low
23	51 to 60 years old	4~5	General	Medium to low
24	18 to 30 years old	6~10	General	High
25	31 to 40 years old	6~10	General	High
26	41 to 50 years old	6~10	General	High
27	51 to 60 years old	6~10	General	Low
28	18 to 30 years old	11~15	General	Low
29	31 to 40 years old	11~15	General	Medium to high
30	41 to 50 years old	11~15	General	Medium to low
31	31 to 40 years old	16~20	General	Medium to high
32	41 to 50 years old	16~20	General	Medium to high
33	51 to 60 years old	16~20	General	Medium to low
34	31 to 40 years old	≥20	General	Low
35	41 to 50 years old	≥20	General	Medium to low
36	51 to 60 years old	≥20	General	Medium to low
37	18 to 30 years old	≤3	Adventure	High
38	41 to 50 years old	≤3	Adventure	Medium to high
39	18 to 30 years old	4~5	Adventure	Medium to high
40	31 to 40 years old	4~5	Adventure	Medium to low
41	41 to 50 years old	4~5	Adventure	Medium to high
42	18 to 30 years old	6~10	Adventure	Medium to high
43	31 to 40 years old	6~10	Adventure	Medium to low
44	41 to 50 years old	6~10	Adventure	Medium to high
45	51 to 60 years old	11~15	Adventure	High
46	41 to 50 years old	16~20	Adventure	Medium to low
47	51 to 60 years old	16~20	Adventure	Medium to high

4. Discussion and Conclusions

4.1. Age Characteristics of Drivers with High Accident Tendency. The age distribution of drivers with high accident risk tendency is mainly concentrated in the age group of 18 to 30 years old. The main accident causation is the driver's illegal driving behaviors, such as robbing road priority and overtaking, and these accidents usually occurred in rush hours. From the perspective of psychological characteristics, young people have strong aggressive psychology, blind self-confidence, and possible expectation imbalance.

4.2. Driving Experience Characteristics of Drivers with High Accident Tendency. From the perspective of the driving experience, the drivers with 6–10 years of driving experience have the highest risk tendency, followed by the drivers with 4–5 years of driving experience. Drivers who have just started driving for 3 years or less are more cautious in their mental preparation, and drivers with more than 10 years of driving experience can deal with all kinds of unexpected situations with all kinds of skills. While a driver who is not senior but has some proficiency in road traffic rules and driving skills will be more risky when overtaking, violating, and so on and consequently has a higher risk tendency to causing accidents.

4.3. Driving Style Characteristics of Drivers with High Accident Tendency. It can be seen from the results that three driving styles of drivers have similar accident risk tendency, and the general drivers should be responsible for the most accidents, which was not agreed with the common recognition that the adventure style drivers will have higher accident rates. The main reasons for this result are as follows: first, the driving style was declared by drivers themselves, there may be subjective interference in the classification of the driver's driving style, people often misjudge themselves, or they do not consider the change of their driving style during their trip, for example, the irregular driving of other vehicles make them feel anger or confusion; second, the accident rate of three styles of drivers would be a better evaluating indicator to indicate the correlation of the driver's driving style with accident risk tendency.

What we need to point out here is that, in this study, only the numbers of drivers in different age groups, driving style groups, and road types are used in statistical analysis, but in fact, drivers in different age groups would have different exposure of driving. Younger or middle-aged drivers may have more traveling miles than teen or older drivers. The number of causalities per mile may be a better indicator than considering only the number of causalities, and different road types also take up different proportions of all the trips. If the exposure of different types can be considered, the importance of intersections could be better explained. But due to the lack of relevant data in the current database, these parameters cannot be obtained right now. Considering the important statistical significance of these parameters, we will further update the procedure of in-depth accident investigation and record more valuable data.

The above research results show that drivers aged 18–30 years are more likely to induce accidents; drivers with 6–10 years of driving experience have the highest risk to accidents; and the driving style is also highly correlated with accident risk. The research on the characters of drivers with high accident risk tendency is conducive to targeted education and prevention of accidents in the future driving training and management.

Data Availability

The data used to support the findings of this study have been deposited in the figshare repository. The link is https://figshare.com/s/bd4d605f61a1bf71fba7.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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