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*Research Article*

# Research on Safety Evaluation of Commercial Vehicle Driving Behavior Based on Data Mining Technology

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The arrival of big data era of internet of vehicles promotes the rapid development of logistics industry, which also indirectly leads to the high traffic accident rate, resulting in huge casualties and property losses. Driving behavior is considered the most central factor leading to traffic accidents. Therefore, a scientific and effective method for evaluating the safety of commercial vehicle driving behavior is urgently needed. In this study, a comprehensive evaluation model of driving behavior security based on multimembership function is proposed, and entropy weight method (EWM), analytic hierarchy process (AHP), and fuzzy comprehensive evaluation algorithm are integrated. Firstly, the evaluation system of commercial vehicle safety of driving behavior is established. Secondly, the weight vector of each evaluation index is determined by combining EW-AHP to eliminate the subjectivity of the traditional AHP algorithm. Then, the fuzzy comprehensive evaluation matrix is calculated based on the multimembership function and fuzzy mathematics theory, and the quantitative evaluation of driving behavior safety is realized based on the matrix. Finally, the real road vehicle driving data and driving behavior data are verified by experiments. The experimental results show that the model can accurately and reasonably evaluate the safety of driving behavior, which is of great significance to improve road traffic safety.

## 1. Introduction

With the rapid development of internet of vehicles technology and big data technology, the logistics industry has developed rapidly [1]. But at the same time, the accident rate of commercial vehicles increases quickly, causing huge casualties and property losses. Driving behavior is generally considered one of the most important factors in crash occurrence [2, 3]. However, due to the stochastic nature of driving, the measurement and modeling of driving behavior remain a challenging topic today. By studying the relationship between driving behavior and accident tendency and exploring the key factors affecting driving risk, the safety of individual driving behavior can be quantitatively evaluated, which is helpful to distinguish safe from unsafe driving and is of great significance for improving road traffic safety [4].

In the safety research field of driving behavior, a large number of researchers have participated and achieved remarkable results. Among them, nonparametric methods and data mining techniques are widely used [5–9]. For example, Chang et al. proposed a classification and regression tree (CART) model to establish the relationship between injury severity, driver/vehicle characteristics, and accident variables, indicating that vehicle type is a very important variable related to the severity of a car accident [5, 6]. Wang et al. characterized the driving risks with the characteristics of sharp deceleration dangerous events and studied the relationship between vehicle motion state, potential collision type, driving environment, driver information,

and driving risk by combining $k$-means clustering and classification regression tree method [7]. Zhu et al. represented the driving risk by the number of historical accidents and studied the relationship between driving behavior, driver information, and accident risk with the method of the multilayer Bayesian network, so as to realize the evaluation of driving behavior safety [8]. Li et al. compared the application of support vector machine (SVM) with the traditional negative binomial model in predicting motor vehicle collision. The results show that SVM is more effective [9]. In addition, Guo et al. assessed the factors associated with individual driver risk using naturalistic driving data [10]. Hong et al. proposed an aggressive driving behavior assessment model based on OBD and smart phone data [11].

In the evaluation model of driving behavior safety, the selection of evaluation index is very important [12]. Jun et al. compared and analyzed the driving behaviors of drivers who had a car accident with those who had not and found that there were significant differences in driving range, driving speed, and acceleration between the two groups [13]. Ayuso et al. found that the longer the distance young drivers travel in speeding, the greater the probability of accidents. This study revealed the relationship between accident tendency and speeding [14, 15]. Bruce et al. believe that the violent braking and starting behaviors during driving are a kind of "high gravity acceleration" event, which can be used to predict the specific type of accidents of young drivers [16]. Research by Omar et al. show that drivers who have experienced traffic accidents have more sudden braking, suggesting that sudden braking may be an indicator of a driver's participation in dangerous traffic conditions [17]. To sum up, driving distance, driving speed, and acceleration are the key indicators that affect the safety of driving behavior.

Previous research with the evaluation of driving behavior safety have focused on passenger vehicles, while there are few studies in the field of commercial vehicles. In addition, the evaluation models proposed by many researchers all focus on distinguishing safe and unsafe driving behaviors and studying the causes affecting unsafe driving behaviors, while there are few researches on quantitative score of the safety of driving behaviors.

In this paper, based on the natural driving data of commercial vehicles, we combine analytic hierarchy process (AHP), entropy weight method (EWM), and fuzzy comprehensive evaluation algorithm to establish a multimembership function fuzzy comprehensive evaluation model of commercial vehicle driving behavior safety. Firstly, EW-AHP is used to determine the weight vector of each evaluation index, and then the fuzzy comprehensive evaluation algorithm model is established. The single-factor membership vector and comprehensive fuzzy evaluation matrix were calculated successively by using fuzzy operation, and the final driving behavior score was determined. Finally, the rationality and validity of the model are verified by experiments. The model can be used not only to analyze factors affecting driving risk and identify driving styles but also to distinguish safe and unsafe driving behaviors and quantify the safety scores of driving behavior.

The paper is outlined as follows. In Section 2, the steps of AHP, EWM, and fuzzy comprehensive evaluation algorithm are introduced briefly. Section 3 proposes a safety evaluation model of commercial vehicle driving behavior, combining the EW-AHP and fuzzy comprehensive evaluation algorithm. In Section 4, the validity of the model is verified based on the natural driving data of commercial vehicles. Section 5 concludes the work and discusses further analysis.

## 2. Theoretical Background

*2.1. Analytic Hierarchy Process (AHP).* AHP is widely used in multiobjective decision problems. It can decompose the elements to be decided into three levels, target, criterion, and index, and conducted qualitative and quantitative analysis on this basis [18]. The steps of AHP algorithm are briefly summarized as follows:

(1) Select evaluation index and establish evaluation system

(2) Construct the comparison scale between each index

(3) Construct a judgment matrix for each level

(4) Verify the consistency of each judgment matrix. If the consistency test fails, step (3) will be returned to modify the judgment matrix. If the consistency test passes, proceed to the next step. In this step, the calculation formula of consistency index $CI$ is as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1}. \tag{1}$$

In formula (1), $\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix, and $n$ is the order of the judgment matrix. Then, the corresponding mean random consistency index $RI$ can be found according to Table 1. Finally, the consistency ratio $CR$ can be calculated by formula (2).

$$CR = \frac{CI}{RI}. \tag{2}$$

When the consistency ratio $CR = 0$, the judgment matrix has complete consistency, and then it passes the consistency test. When $CR < 0.1$, the judgment matrix has satisfactory consistency, and then it passes the consistency test. When $CR > 0.1$, the judgment matrix does not have consistency, and the consistency test does not pass, so the judgment matrix needs to be modified.

(5) Calculate weight vector of each index

(6) Complete the evaluation of the goal.

*2.2. Entropy Weight Method (EWM).* EWM is an objective method to calculate the weight. In information theory, entropy is a way to measure the uncertainty of events. The greater the uncertainty of the event, the greater the entropy and the more information it contains. The smaller the

Table 1: Mean random consistency index.

| $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| $RI$ | 0.00 | 0.00 | 0.52 | 0.89 | 1.12 | 1.26 | 1.36 |

uncertainty of the event, the smaller the entropy and the smaller the information contained [19].

According to the characteristics of entropy, the randomness and disorder degree of an event can be judged by calculating the entropy value, and the dispersion degree of an index can also be judged by the entropy value. The greater the dispersion degree of an index, the greater the influence (weight) of the index on the evaluation target will be; otherwise, the less it will be [20]. The steps of EWM algorithm are briefly summarized as follows:

(1) Import the data that need to calculate the entropy weight

(2) Standardize the data matrix

It is assumed that the data matrix consisting of $n$ objects to be evaluated and $m$ evaluation indexes is as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}. \tag{3}$$

Since the meanings of positive and negative indicators are different, different formulas are needed for data standardization processing of positive and negative indicators. Formula (4) for standardization of positive indicators and formula (5) for standardization of negative indicators are as follows:

$$z_{ij} = \frac{x - \min\left\{x_{1j}, \cdots, x_{nj}\right\}}{\max\left\{x_{1j}, \cdots, x_{nj}\right\} - \min\left\{x_{1j}, \cdots, x_{nj}\right\}}, \tag{4}$$

$$z_{ij} = \frac{\min\left\{x_{1j}, \cdots, x_{nj}\right\} - x_{ij}}{\max\left\{x_{1j}, \cdots, x_{nj}\right\} - \min\left\{x_{1j}, \cdots, x_{nj}\right\}} \tag{5}$$

(3) Calculate the sample specific gravity

Calculate the proportion of the $i$th sample in the $j$th index and regard it as the probability used in the calculation of relative entropy. Calculated from the previous step, the normalized matrix $Z$ is

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m} \\ z_{21} & z_{22} & \cdots & z_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nm} \end{bmatrix}. \tag{6}$$

The probability matrix $P$ can be calculated, where the calculation formula of each element $p_{ij}$ is as follows:

$$P_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}}, i = 1 \cdots n, j = 1 \cdots m \tag{7}$$

(4) Calculate information entropy and information utility values of each index

For the $j$th index, its information entropy is calculated as shown in Formula (8), and its information utility value is calculated as shown in formula (9).

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij} \ln\left(p_{ij}\right), j = 1, \cdots, m, \tag{8}$$

$$d_j = 1 - e_j, j = 1, \cdots, m \tag{9}$$

(5) Calculate the entropy weight of each index.

The calculation formula of entropy weight of each index is as follows:

$$V_j = \frac{d_j}{\sum_{i=1}^{n} d_j}, j = 1, \cdots, m. \tag{10}$$

*2.3. Fuzzy Comprehensive Evaluation Algorithm.* Fuzzy comprehensive evaluation is a method to quantify a number of influence factors with unclear boundaries and difficult to be quantified, and to conduct comprehensive evaluation of the grade status of the evaluated object from multiple factors [21, 22]. The steps of fuzzy comprehensive evaluation algorithm are briefly summarized as follows:

(1) Establish the factor set of each evaluation index (factors set)

(2) Determine the evaluation grade of the object to be evaluated (evaluation set)

(3) Determine the weight vector of each evaluation index

(4) Determine the membership function. The commonly used membership functions include the Gaussian function, ridge function, and rectangle function. Their formula is as follows:

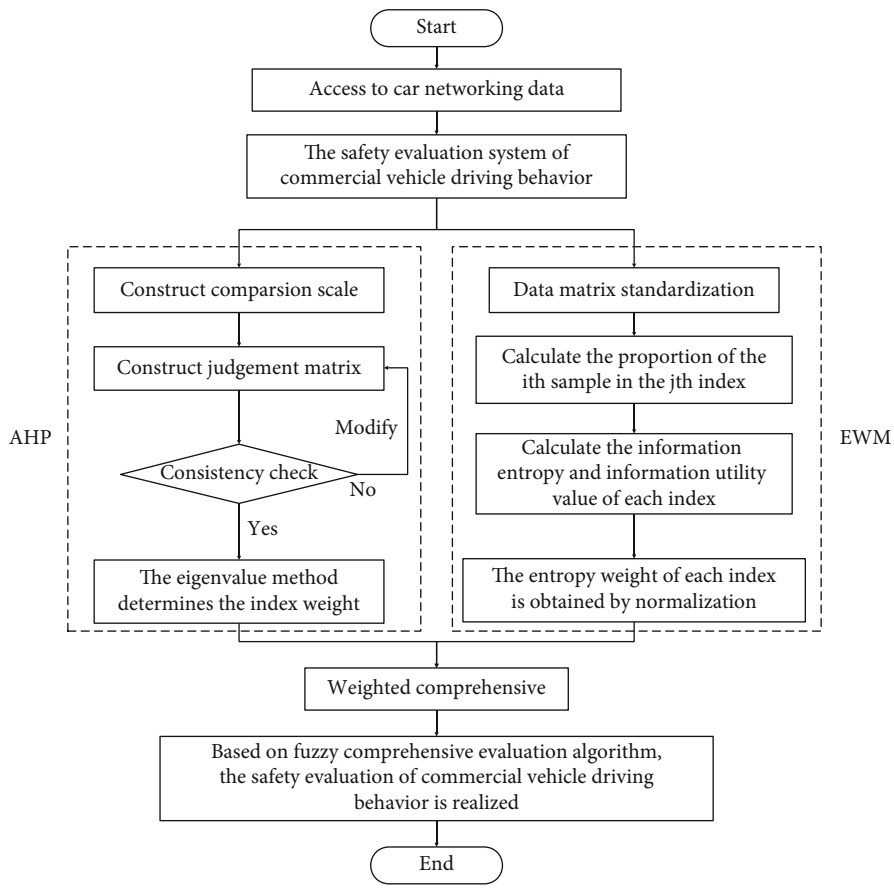


Figure 1: Overall algorithm flow chart.

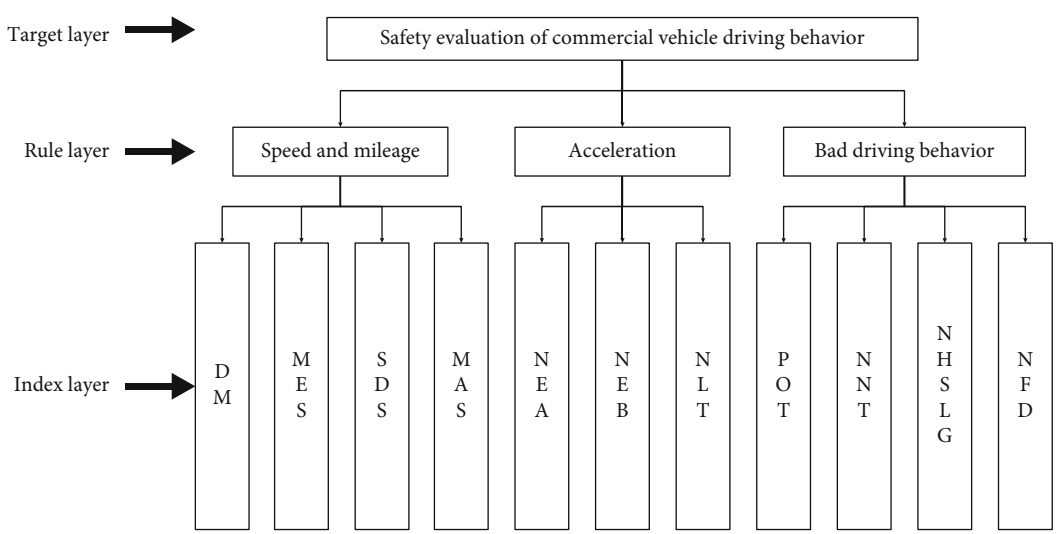


Figure 2: Safety evaluation index system of commercial vehicle driving behavior.

Gaussian function (minimum type, intermediate type, and maximum type):

$$r(x) = \begin{cases} 1, & x \le a \\ e^{-((x-a)/\sigma)^2} & x > a, \end{cases} \tag{11}$$

$$r(x) = \begin{cases} 0, & x \le a \\ 1 - e^{-((x-a)/\sigma)^2} & x > a, \end{cases} \tag{12}$$

$$r(x) = e^{-((x-a)/\sigma)^2}, -\infty < x < +\infty. \tag{13}$$

Table 2: Judgment matrix of criterion layer $U$.

| $U$ | $U_1$ | $U_2$ | $U_3$ |
|---|---|---|---|
| $U_1$ | 1 | 3 | 4 |
| $U_2$ | 1/3 | 1 | 2 |
| $U_3$ | 1/4 | 1/2 | 1 |

Ridge function (minimum type, intermediate type, and maximum type):

$$r(x) = \begin{cases} 1, & x \le a \\ \frac{1}{2} - \frac{1}{2} \sin \frac{\pi}{b-a}\left(x - \frac{a+b}{2}\right), & a < x < b \\ 0, & x \ge b, \end{cases} \tag{14}$$

$$r(x) = \begin{cases} 0, & x \le a \\ \frac{1}{2} + \frac{1}{2} \sin \frac{\pi}{b-a}\left(x - \frac{a+b}{2}\right), & a < x < b \\ 1 & b < x \le c \\ \frac{1}{2} - \frac{1}{2} \sin \frac{\pi}{d-c}\left(x - \frac{c+d}{2}\right), & c < x < d \\ 0, & x \ge d, \end{cases} \tag{15}$$

$$r(x) = \begin{cases} 0, & x \le a \\ \frac{1}{2} + \frac{1}{2} \sin \frac{\pi}{b-a}\left(x - \frac{a+b}{2}\right), & a < x < b \\ 1, & x \ge b. \end{cases} \tag{16}$$

Rectangle function (minimum type, intermediate type, and maximum type):

$$r(x) = \begin{cases} 1, & x \le a \\ 0, & x > a, \end{cases} \tag{17}$$

$$r(x) = \begin{cases} 0, & x < a \\ 1, & x \ge a, \end{cases} \tag{18}$$

$$r(x) = \begin{cases} 0, & x < a \\ 1, & a \le x < b \\ 0, & x \ge b \end{cases} \tag{19}$$

(5) The fuzzy comprehensive evaluation matrix is obtained

Firstly, formula (20) is used to calculate the single-factor membership vector, and formula (21) is used to calculate the multifactor membership matrix.

$$R_i = W_k \odot r_i, \tag{20}$$

Table 3: Judgment matrix of index layer $U_1$.

| $U_1$ | $U_{11}$ | $U_{12}$ | $U_{13}$ | $U_{14}$ |
|---|---|---|---|---|
| $U_{11}$ | 1 | 1/3 | 1/2 | 1 |
| $U_{12}$ | 3 | 1 | 2 | 2 |
| $U_{13}$ | 2 | 1/2 | 1 | 1 |
| $U_{14}$ | 1 | 1/2 | 1 | 1 |

Table 4: Judgment matrix of index layer $U_2$.

| $U_2$ | $U_{21}$ | $U_{22}$ | $U_{23}$ |
|---|---|---|---|
| $U_{21}$ | 1 | 1 | 2 |
| $U_{22}$ | 1 | 1 | 3 |
| $U_{23}$ | 1/2 | 1/3 | 1 |

Table 5: Judgment matrix of index layer $U_3$.

| $U_3$ | $U_{31}$ | $U_{32}$ | $U_{33}$ | $U_{34}$ |
|---|---|---|---|---|
| $U_{31}$ | 1 | 1/2 | 1/2 | 1/2 |
| $U_{32}$ | 2 | 1 | 2 | 1 |
| $U_{33}$ | 2 | 1/2 | 1 | 1/2 |
| $U_{34}$ | 2 | 1 | 2 | 1 |

Table 6: Weight summary results of EW-AHP combination.

| Indicators | $U_1$ (0.1311) | $U_2$ (0.5267) | $U_3$ (0.3422) | The comprehensive weights |
|---|---|---|---|---|
| $U_{11}$ | 0.5805 | | | 0.0761 |
| $U_{12}$ | 0.2677 | | | 0.0350 |
| $U_{13}$ | 0.1379 | | | 0.0181 |
| $U_{14}$ | 0.0149 | | | 0.0020 |
| $U_{21}$ | | 0.2262 | | 0.1191 |
| $U_{22}$ | | 0.6632 | | 0.3493 |
| $U_{23}$ | | 0.1106 | | 0.0583 |
| $U_{31}$ | | | 0.1977 | 0.0677 |
| $U_{32}$ | | | 0.1876 | 0.0642 |
| $U_{33}$ | | | 0.2622 | 0.0897 |
| $U_{34}$ | | | 0.3524 | 0.1206 |

$$R = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_m \end{bmatrix}. \tag{21}$$

In formula (20), $R_i$ is a single-factor membership vector. The basic principle is derived from the fuzzy transformation $\odot$ of the weight vector corresponding to $r_i$ (the

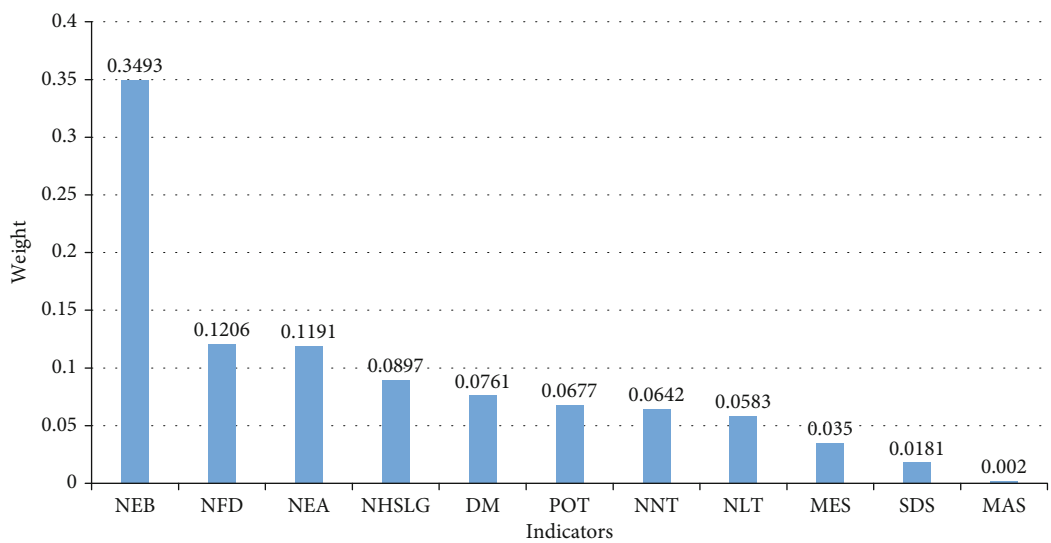


Figure 3: The weight of each index.

membership degree of the $i$th index for each evaluation level) and the second-level index, The selected fuzzy operator [23, 24] is $(\bullet+)$, $1 \le k \le 3$, $1 \le i \le m$.

$$S = W \odot R = (W_1, W_2, W_3) \odot \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}. \tag{22}$$

$S$ is the fuzzy comprehensive evaluation matrix, $W$ is the weight vector of driving behavior evaluation index determined by formula (23), and $R$ is the multifactor membership matrix determined by formula (21). The operator symbol is the fuzzy operator $(\bullet+)$. Based on the above algorithm steps, the quantitative evaluation of commercial vehicle driving behavior safety can be realized.

(6) Quantify and score your goals.

## 3. Proposed Ensemble Method

The subjectivity of traditional AHP algorithm can be eliminated by combining the three methods in the second section and using the entropy weight analytic hierarchy process to comprehensively assign weights to each evaluation index. Then, the fuzzy comprehensive evaluation algorithm is used to score the driving behavior quantitatively. The flow chart of the overall algorithm is shown in Figure 1.

*3.1. Establish the Safety Evaluation System of Commercial Vehicle Driving Behavior.* Referring to Section 1, we can know that the driving mileage, driving speed, and acceleration are the key indicators affecting the safety of driving behavior. We can extend some other indicators from these three indicators, such as driving mileage, mean speed, overspeed, standard deviation of speed, maximum speed, emergency acceleration, and emergency braking. However, in the field of commercial vehicles, there are a large number of bad driving behaviors such as large throttle, low gear and high speed, neutral taxiing, and fatigue driving. Therefore, we also choose the above indicators.

Of course, the indicators affecting the driving safety are far more than this. Indicators such as weather, road conditions, driver age, and gender will have a certain impact on driving safety. However, the main research object of this paper is the driver's driving behavior, so these indicators are not within the scope of consideration.

Table 7: Corresponding scores of each rating level.

| Road conditions | Rating | | | | |
|---|---|---|---|---|---|
| | Excellent | Good | Average | Poor | Very poor |
| Urban road | 90 | 70 | 50 | 30 | 10 |
| The highway | 90 | 80 | 60 | 45 | 25 |
| Mixed road | 85 | 65 | 45 | 25 | 5 |

Table 8: Selection scheme of multimembership function.

| | |
|---|---|
| Driving mileage (DM) | Gaussian function |
| Mean speed (MES) | |
| Standard deviation of the speed (SDS) | |
| Maximum speed (MAS) | Ridge function |
| Number of emergency acceleration (NEA) | |
| Number of emergency braking (NEB) | Rectangle function |
| Number of large throttle (NLT) | |
| Proportion of overspeed time (POT) | Ridge function |
| Number of neutral taxiing (NNT) | |
| Number of high speed in low gear (NHSLG) | |
| Number of fatigue driving (NFD) | Rectangle function |

Table 9: Reference values of membership degrees of each indicator to each grade.

| Indicator | Coefficient | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ | $x_7$ | $x_8$ | $x_9$ |
| DM | 50 | 155 | 260 | 365 | 470 | 575 | 680 | 785 | 1000 |
| MES | 66 | 69 | 72 | 75 | 78 | 81 | 84 | 87 | 90 |
| SDS | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | — |
| MAS | 88 | 92 | 95 | 97 | 99 | 101 | 103 | 105 | — |
| NEA | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | — |
| NLT | 5 | 20 | 35 | 50 | 65 | 80 | 95 | 110 | — |
| POT | 0 | 0.005 | 0.020 | 0.035 | 0.050 | 0.065 | 0.080 | 0.100 | — |
| NNT | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | — |
| NHSLG | 0 | 2 | 4 | 6 | 8 | 10 | 12 | 14 | — |

Table 10: Vehicle driving data.

| Data generation time | Latitude and longitude | Speed (km/h) | Rotate speed (rpm) | Accumulated distance (km) | Acceleration ($m/s^2$) | Time (h) |
|---|---|---|---|---|---|---|
| 2020-8-1 0:00 | 114.9279 \| 31.9632 | 36.0 | 1166.000 | 22255.4 | 0.30 | 271.5 |
| 2020-8-1 0:00 | 114.9282 \| 31.9641 | 47.6 | 1211.125 | 22255.6 | 0.41 | 271.5 |
| 2020-8-1 0:00 | 114.9287 \| 31.9653 | 56.7 | 1114.125 | 22255.7 | 0.30 | 271.5 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 2020-8-31 23:59 | 125.4410 \| 43.9755 | 97.3 | 1190.125 | 54854.7 | -0.09 | 697.8 |
| 2020-8-31 23:59 | 125.4425 \| 43.9734 | 93.3 | 1147.125 | 54854.9 | -0.06 | 697.8 |

In addition, considering too many factors in the model is not conducive to the development of subsequent analysis, so we chose the key indicators identified above.

Therefore, the safety evaluation system of commercial vehicle driving behavior shown in Figure 2 can be established. Among them, the target layer is the safety evaluation of commercial vehicle driving behavior ($U$). The criteria layer includes speed and mileage ($U_1$), acceleration ($U_2$), and bad driving behavior ($U_3$). There are 11 indicators ($U_{11} - U_{34}$) in the index layer; they are the driving mileage (DM), mean speed (MES), standard deviation of the speed (SDS), maximum speed (MAS), number of emergency acceleration (NEA), number of emergency braking (NEB), number of large throttle (NLT), proportion of overspeed time (POT), number of neutral taxiing (NNT), number of high speed in low gear (NHSLG), and number of fatigue driving (NFD).

*3.2. Determination of Index Weight Based on AHP.* Based on the SATTY1-9 scale method [25] and the opinions of senior experts in the automobile industry, the judgment matrix of each index layer can be obtained as shown in Tables 2–5.

According to formulas (1) and (2) and judgment matrix of each indicator layer, it can be calculated that that the consistency ratio ($CR$) of judgment matrix of each indicator layer is less than 0.1, satisfying the consistency. Therefore, the maximum eigenvalue of the consistent matrix and its corresponding eigenvector can be obtained, which can represent the importance degree of each index layer, namely, weight allocation.

Therefore, the weight vector of each level index can be calculated by the MATLAB programming. The weight vector of criterion layer $U$ is [0.6250, 0.2385, 0.1365]. The weight vector of indicator layer $U_1$ is [0.1484, 0.4258, 0.2312, 0.1945]. The weight vector of indicator layer $U_2$ is [0.3874, 0.4434, 0.1692]. The weight vector of indicator layer $U_3$ is [0.1404, 0.3300, 0.1996, 0.3300]. The comprehensive weight vector of each indicator layer $w = [0.0928, 0.2661, 0.1445, 0.1216, 0.0924, 0.1058, 0.0404, 0.0192, 0.0450, 0.0272, 0.0450]$.

*3.3. Determine the Index Weight Based on Entropy Weight Method (EWM).* Combined with formulas (3)–(10), the weight of each index can be calculated by the MATLAB programming as follows: $v = [0.0371, 0.0007, 0.0286, 0.0386, 0.0263, 0.0631, 0.1438, 0.1292, 0.0662, 0.1035, 0.1635, 0.1993]$.

*3.4. EW-AHP Combination Weights.* Based on the weights obtained by the AHP and EWM algorithm in Sections 3.2 and 3.3, respectively, the combined weights of evaluation indexes can be calculated according to the following formula:

Table 11: Driving behavior data.

| Start time | End time | Vehicle type | Bad driving behavior | The last time (s) | Alarm location (latitude and longitude) |
|---|---|---|---|---|---|
| 2020-8-1 1:43 | 2020-8-1 1:43 | Tractor | Large throttle | 8 | 115.7339 \| 37.6072 |
| 2020-8-1 3:12 | 2020-8-1 3:12 | Tractor | Large throttle | 8 | 115.1235 \| 36.5906 |
| 2020-8-1 3:39 | 2020-8-1 3:39 | Tractor | Large throttle | 8 | 115.1118 \| 36.2635 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 2020-8-31 23:12 | 2020-8-31 23:12 | Tractor | Sudden braking | 1 | 113.2730 \| 23.4528 |
| 2020-8-31 23:13 | 2020-8-31 23:13 | Tractor | Neutral taxiing | 6 | 113.2775 \| 23.4523 |

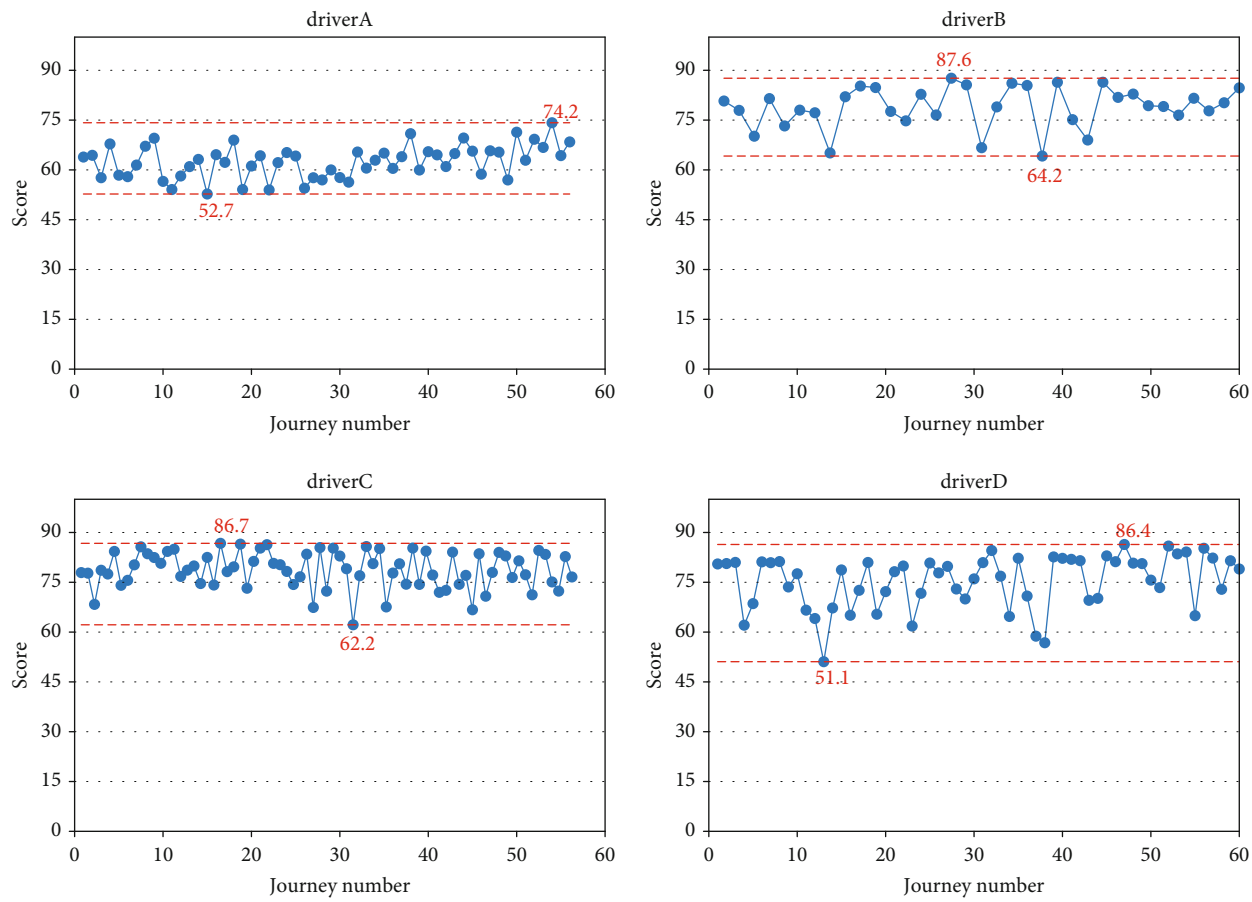


Figure 4: The scoring results of the top four drivers.

$$W_i = \frac{w_i v_i}{\sum_{i=1}^{n} w_i v_i}, i = 1, \cdots, n. \tag{23}$$

In Sections 3.2 and 3.3, $w$ is the weight of each evaluation index calculated based on AHP, and $v$ is the weight of each evaluation index calculated based on EWM. According to formula (23), the combined EW-AHP weight summary results can be obtained, as shown in Table 6.

In order to better analyze the weight proportion of each index, the weight bar chart of each evaluation index can be drawn, as shown in Figure 3. As can be seen from Figure 3, sudden braking is the most critical factor affecting the safety of commercial vehicle driving behavior, and the second factor is fatigue driving and rapid acceleration. Therefore, the improvement of the safety of commercial vehicles' driving behavior should be started from the following three aspects: emergency braking, fatigue driving, and rapid acceleration.

*3.5. Fuzzy Comprehensive Evaluation Algorithm and Implementation.* Section 2.3 has briefly introduced the steps of fuzzy comprehensive evaluation algorithm. This section will introduce in detail the specific implementation of the application of the Fuzzy comprehensive evaluation algorithm based on the EW-AHP combination weight to the safety evaluation of commercial vehicle driving behavior.

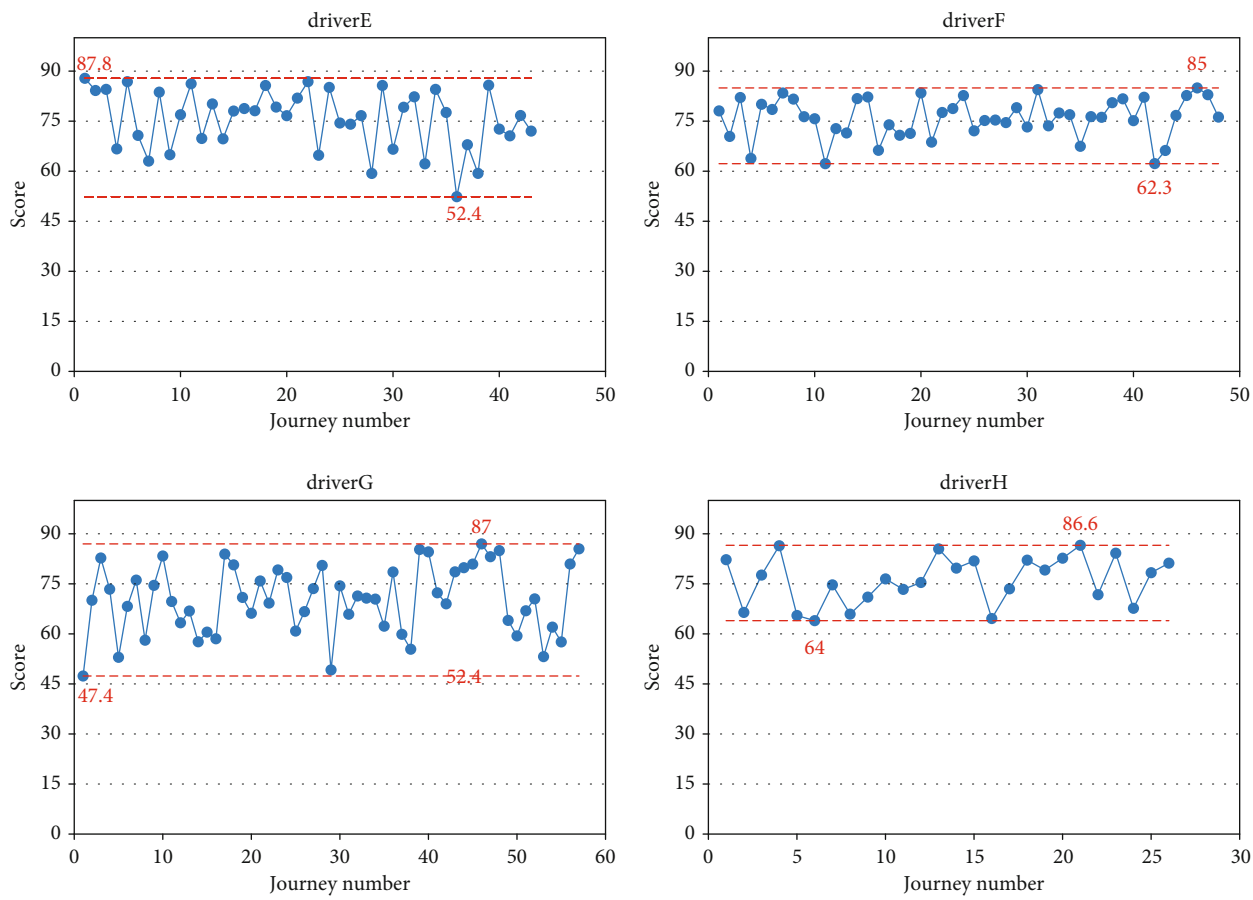


Figure 5: Scoring results of the last four drivers.

Table 12: Driver E score difference table.

| Indicators | Journey number | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 36 | 33 | 42 | 35 | 17 | 39 | 11 | 5 |
| DM | 748.7 | 329.2 | 102.4 | 253.4 | 278.2 | 198.8 | 174 | 197.4 |
| NEA | 34 | 11 | 6 | 5 | 2 | 2 | 0 | 0 |
| NEB | 2 | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| POT | 0.03 | 0.02 | 0.00 | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 |
| NHSLG | 80 | 2 | 0 | 0 | 1 | 2 | 4 | 0 |
| NFD | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Score | 52.36 | 62.21 | 76.69 | 77.61 | 78.12 | 85.78 | 86.22 | 86.84 |

*3.5.1. Establish Driving Behavior Factors Set for Commercial Vehicles.* According to Figure 2, the factor set can be established as follows:

$$\begin{aligned} U &= \{U_1, U_2, U_3\}, \\ U_1 &= \{U_{11}, U_{12}, U_{13}, U_{14}\}, \\ U_2 &= \{U_{21}, U_{22}, U_{23}\}, \\ U_3 &= \{U_{31}, U_{32}, U_{33}, U_{34}\}. \end{aligned} \tag{24}$$

*3.5.2. Establish Evaluation Set on Commercial Vehicle Driving Behavior.* In order to quantify the final driving behavior evaluation score between 0 and 100, it is necessary to determine the corresponding score of each evaluation level while determining the evaluation set. Therefore, the evaluation set on the driving behavior of commercial vehicles can be established as follows:

$$V = \{\text{Excellent, Good, Average, Poor, Very Poor}\}. \tag{25}$$

The corresponding scores of each rating level can be established according to different driving conditions, as shown in Table 7.

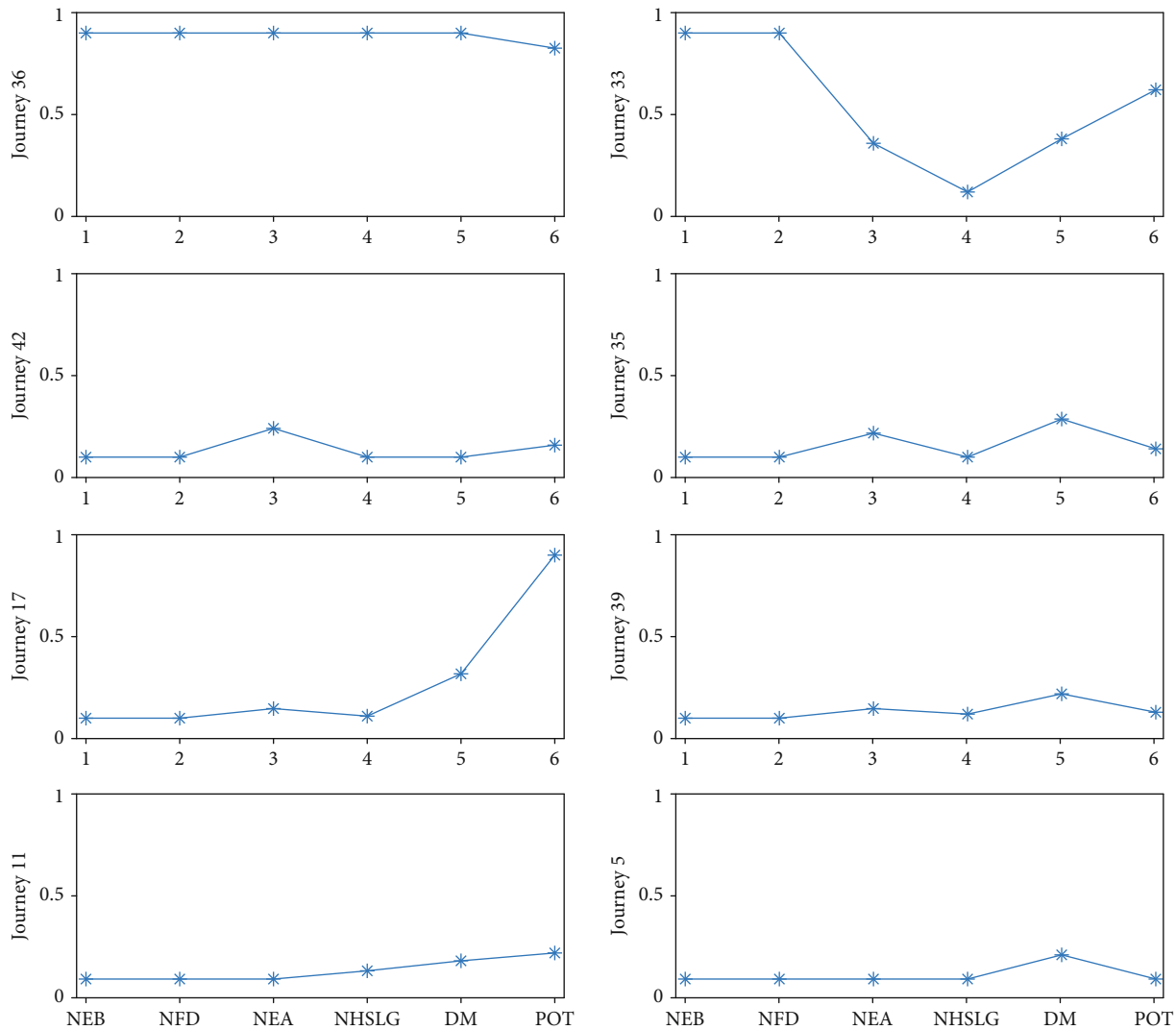


Figure 6: Data normalization results of driver E.

*3.5.3. Determine the Weight Vector of Each Evaluation Indicator.* According to Table 6, the normalized result of index weight is:

$$\begin{aligned} W &= (0.1311, 0.5267, 0.3422), \\ W_1 &= (0.5805, 0.2677, 0.1379, 0.0149), \\ W_2 &= (0.2262, 0.6632, 0.1106), \\ W_3 &= (0.1977, 0.1876, 0.2622, 0.3524). \end{aligned} \tag{26}$$

*3.5.4. Determine the Membership Function.* Due to the different characteristics of each evaluation index, the membership of each index cannot be reasonably explained by using only one membership function. Therefore, this paper proposes a method of using multiple membership functions to explain the membership of the selected evaluation index separately. After repeated experiments and comparisons of membership functions, the selection scheme of multiple membership functions as shown in Table 8 was finally determined.

In Equations (11)–(19), the parameters $a$, $b$, $c$, and $d$ are replaced by $x_i$. The reference value of membership function is different for different indicators. The calculation formula of reference value of membership degree of each indicator is as follows:

$$I_i(x_i) = \text{mean}(I_i) \pm |5 - i| \times \text{STD}(I_i). \tag{27}$$

In formula (27), if $i$ is less than 5, it takes a negative sign; otherwise, it takes a positive sign. $I_i(x_i)$ is the reference value of the membership degree of the $i$th grade of the $i$th index, $\text{mean}(I_i)$ is the mean of the data column in which the $i$th index is located, and $\text{STD}(I_i)$ is the standard deviation of the data column of the $i$th index.

For the reference value of membership degree of driving mileage, we divide its maximum value and minimum value into equal parts. The other indexes are calculated according to formula (27) and then dynamically adjusted. The reference values of each index to each grade of membership are shown in Table 9.

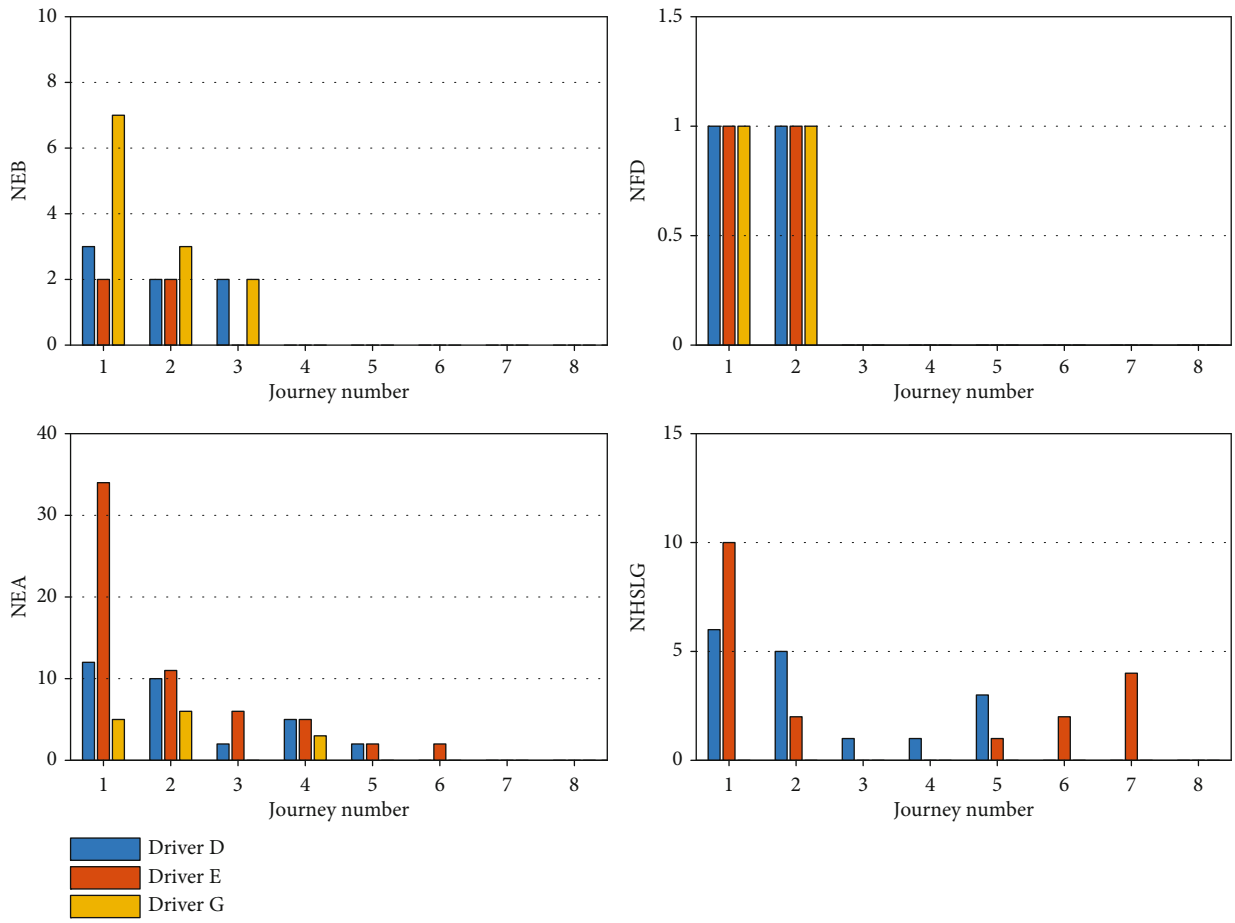


Figure 7: Comparison chart of the first 6 indicators.

Because the number of emergency braking and fatigue alarm is the rectangle function (with fewer parameters), it is different from the other two membership functions. According to the different data characteristics, the membership scheme of the two indexes is as follows: if the number of emergency braking is zero times, it belongs to the excellent level; if one time, it belongs to the good level; if two times, it belongs to the average level; if three times, it belongs to the poor level; if over three times, it belongs to the very poor level. If the number of fatigue alarm is zero times, it is classified as excellent, one time is poor, and more than one time is very poor. Finally, according to formulas (20)–(22), the fuzzy comprehensive evaluation matrix can be calculated to achieve the quantitative scoring of commercial vehicle driving behavior.

## 4. Validation and Results

The vehicle driving data of several sections of a company in August were selected, including "Hangzhou-Harbin," "Guangzhou-Changchun," and "Guangzhou-Hefei." Then, the vehicle travel data was divided into various journeys (the engine running from start to stop and the driving distance greater than 10 km was classified as a complete journey). All the travel data of 8 drivers within one month were selected from these three roads, and a total of 403 complete journeys were divided. The original driving data and driving behavior data of one of the drivers are shown in Tables 10 and 11.

The quantitative scoring model of commercial vehicle driving safety established in this study can calculate the scores of 8 drivers, and the results are shown in Figures 4 and 5.

By comparing the final scores of the eight drivers, it can be seen that the scores of driver A are generally low, and the scores are stable without great fluctuations. Therefore, we can think that the driving style of driver A belongs to the nonstandard driving type with low driving safety; however, driver B, driver C, driver F, and driver H have relatively high overall and stable scores. Therefore, we can conclude that they have normative and stable driving styles with high driving safety. The scores of driver D, driver E, and driver G are both high and low, and the scores fluctuate greatly. Therefore, it can be considered that the driving styles of them belong to the random type of driving with unstable driving safety. The final driving behavior score obtained by referring to the comprehensive evaluation model can standardize the driving style of nonstandard drivers and encourage drivers to maintain the standard driving, which is conducive to improve the safety of road traffic.

As can be seen from Figure 3, the total weight of the first six indicators exceeds 80%, so the analysis of these six

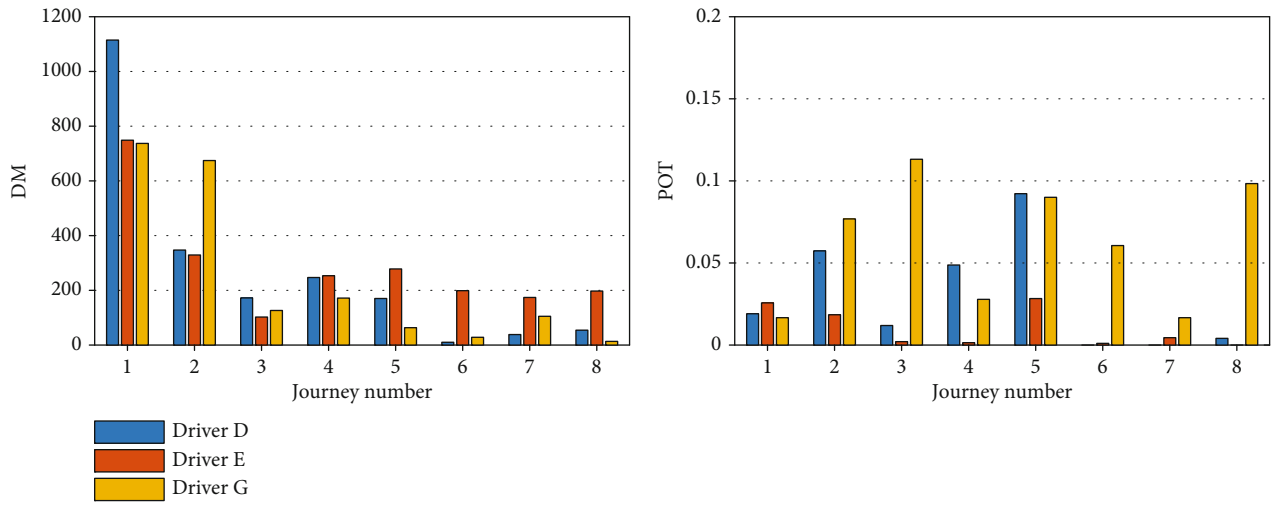


Figure 8: Comparison chart of the last 5 indicators and scores.

indicators is sufficient to prove the rationality of our evaluation model. We choose drivers D, E, and G whose scores fluctuated greatly for in-depth analysis. For the analysis of a single driver, such as driver E, we selected 8 journeys with significant differences. The scores of the 8 journeys are shown in Table 12. In order to better verify our model, each indicator in Table 12 is normalized, and the line diagram as shown in Figure 6 can be drawn.

As can be seen from Figure 6, for journeys with low scores (such as journeys 36 and 33), they have a poor performance in indicators with high weight (such as emergency braking and fatigue driving), so they have the lowest score. On the contrary, for journeys with high scores (such as journeys 39, 11, and 5), they perform well in all indicators and thus have higher scores. For journeys with medium scores (such as journeys 42, 35, and 17), they performed more modestly (neither too much nor too little) on all indicators and so scored moderately. By analyzing all the journeys of the other seven drivers, we can find that their scores were consistent with our analysis.

By comparing the 8 journeys with significantly different scores of drivers D, E, and G, a multidriver score comparison diagram can be drawn, as shown in Figures 7 and 8. Among them, low-scoring journeys include journeys 1 and 2, medium-scoring journeys include journeys 3, 4, and 5, and high-scoring journeys include journeys 6, 7, and 8.

Figures 7 and 8 compared and analyzed the scores of drivers D, E, and G. It is obvious that the three drivers perform poorly in various driving behavior indicators of journeys 1 and 2 (such as a large amount of emergency braking, emergency acceleration, and fatigue driving), so the score is low. With the decrease of bad driving behavior performance, the score increases accordingly. Therefore, our model can reasonably achieve the quantitative evaluation of the safety of commercial vehicle driving behavior.

## 5. Conclusion

In this study, a commercial vehicle driving safety evaluation model combining EW-AHP and fuzzy comprehensive evaluation algorithm is proposed as a method basis for studying the relationship between driving risks, risk causes, and quantification of driving behaviors. Based on the natural driving data of commercial vehicles, a safety evaluation system for commercial vehicle driving behavior based on AHP was established, which combines four main aspects of driving behavior characteristics including driving mileage, driving speed, acceleration, and bad driving behavior.

Based on EW-AHP, the weight coefficient of each evaluation index is effectively determined, which solves the problem that the traditional AHP algorithm is too subjective and finds out the key causes affecting the driving risk, which are emergency braking, fatigue driving, and rapid acceleration, respectively. In view of the different characteristics of each evaluation index, it is hard to explain the membership of each index by using only one membership function. Therefore, a method to explain the membership of each evaluation index by using the multimembership function is proposed. Compared with previous studies, this model can not only distinguish safe and unsafe drivers but also identify driving styles and achieve quantitative scoring of driving behavior safety. The model is tested by using the actual driving data of multiple sections and the effectiveness of the proposed method is verified.

The results of this study can be used to quantitatively evaluate the driving behavior of commercial vehicle drivers, standardize driving, and help drivers develop good driving habits to improve road traffic safety. In the future research, there are still some limitations and improvements worth noting. For example, although this study is based on multiple roads driving data, the data of roads can be more comprehensive and extensive. In addition, the research scope can not only be limited to drivers' driving behaviors but also include more factors (such as environmental factors, roads, and drivers' emotions).

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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