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Research on a Comprehensive Evaluation System for Driving Behavior by Introducing Fuzzy Evaluation Based on Natural Driving Data

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Abstract

Scientific evaluation of driving behavior can provide feasible suggestions for improving driver operating habits, improving driving safety, and reducing energy consumption. It is also of great significance for the development of autonomous driving functions. The existing evaluation methods for driving behavior have shortcomings such as subjectivity and randomness, and neglect the ambiguity of human judgment. This article proposes an overall evaluation system based on the extension analytic hierarchy process based on real driving data collected from real vehicles. Grey clustering and fuzzy comprehensive evaluation are introduced to evaluate the driving behavior of drivers from four key indicator dimensions, effectively improving the accuracy and scientificity of driving behavior evaluation.

Keywords: Driving behavior evaluation; Natural driving data; Fuzzy evaluation

Introduction

With the rapid development of the automotive industry, the number of cars in China is gradually increasing. However, drivers' awareness of traffic civilization and safety precautions is clearly lagging behind, and traffic violations such as speeding, rear end collisions, and not giving way according to regulations are frequent. Drivers, as the operators of vehicles, are the main participants in the road traffic system, and therefore their driving behavior is receiving increasing attention. Driving behavior refers to the physical behavior formed by the driver's brain analysis by perceiving the constantly changing traffic conditions of vehicles, roads, traffic signals, etc. around them through sensory organs such as hearing and vision [1]. Mainly reflected in the control of vehicle speed and driving direction. As the driver's driving experience increases, driving behavior will form a long-standing driving style, namely driving behavior habits. Studying and evaluating driving behavior is important for improving traffic environment, road safety, and other issues.

At present, the commonly used methods for evaluating driving behavior by domestic and foreign scholars can be roughly divided into two categories: artificial intelligence methods and traditional evaluation methods. Representative ones are as follows: Raunask Bhattachary and Blake Wulfe et al. modeled human driving as a sequential decision problem, which is characterized by nonlinearity and randomness, and unknown potential cost function. Based on the work of reverse reinforcement learning (IRL), they generated resistance imitative learning (GAIL) to model human driving [2]; Lin X et al. collected driver's driving behavior data and obtained the characteristic frequency domain of different driving behaviors from it. Then, based on the frequency domain of driving behavior characteristics, they constructed a driving behavior evaluation model for quantitative evaluation of driving behavior [3]; Ma Cong and Zhang Zhihong et al. used the vehicle condition data collected by OBD (On Board Diagnostic) to construct driving behavior evaluation models using AHP and AEW-AHP entropy weight analytic hierarchy process to evaluate the driver's driving behavior, and proposed feasible suggestions for improving the driver's driving habits [4, 5]; Liu Kaili, Bai Dong, and others used decision tree and support vector machine models to evaluate driving behavior [6, 7].

From the current status of driving behavior evaluation, it can be seen that the commonly used driving behavior evaluation methods have obvious shortcomings, mainly reflected in constructing a judgment matrix through precise values, numerical stereotypes are not elastic, and seriously ignore the ambiguity that people have in making judgments, which has a serious impact on the scientific rationality of the evaluation results. In response to the above issues, this article proposes a comprehensive evaluation method for driving behavior, which uses the extension analytic hierarchy process to construct the overall evaluation system. The combination weighting method based on the fusion of extension analytic hierarchy process and entropy weighting method is introduced in the determination of weights, and grey clustering and fuzzy comprehensive evaluation are introduced at each level of the rating system, Overcoming some shortcomings of commonly used evaluation methods in evaluating driving behavior.

Materials & Methods

Theoretical Basis Methods

Extension Analytic Hierarchy Process

He extension analytic hierarchy process (AHP) is based on the traditional AHP analytic hierarchy process. By using extension theory to replace accurate values with interval range values when constructing a judgment matrix, it can effectively avoid the shortcomings of the traditional AHP analytical hierarchy process [8]. The form of the interval number used is $[r_{ij}-\delta, r_{ij}+\delta]$, where: r_{ij} refers to the midpoint of the interval determined by the (1~9) scaling method. The specific process of weight calculation based on the extension analytic hierarchy process is as follows:

Firstly, use the interval range calculated by the scaling method to determine the extension judgment matrix A . Therefore, the constructed matrix is a positive and reciprocal matrix A , where $a_{ij} = < a_{ij}^-, a_{ij}^+ >$;

Secondly, construct maximum/minimum value judgment matrices A^- and A^+, resulting in maximum value judgment matrix $A^+ = [a_{ij}^+]$and minimum value judgment matrix $A^- = [a_{ij}^-]$. Calculate the maximum eigenvalues of the maximum/minimum value judgment matrix, and use normalization methods to process the feature vectors that match their respective maximum eigenvalues. Record the processed feature vectors as x^+ and x^-, respectively;

Calculate the weight vector of the extension interval,

$$S = (S_1, S_2, \ldots, S_n) = < kx^-, mx^+ > \qquad (1)$$

Among them,

$$k = \sqrt{\sum_{j=1}^{m} \frac{1}{\sum_{i=1}^{m} a_{ij}^+}}, \quad m = \sqrt{\sum_{j=1}^{m} \frac{1}{\sum_{i=1}^{m} a_{ij}^-}} \qquad (2)$$

Finally, calculate the weight vector

If $S_i = < S_i^-, S_i^+ >$, $S_j = < S_j^-, S_j^+ >$, and are given weights $U_j = 1$, then the weights can be calculated using equation (3):

$$U_i = \frac{2(S_i^+ - S_j^-)}{(S_j^+ - S_j^-) + (S_i^+ - S_i^-)} \qquad (3)$$

Entropy weight method

The entropy weight method mainly reflects the importance of indicators by the amount of information contained in indicator data, and determines the weight size of indicators based on the form of entropy value [9]. The more information the indicator data contains, the smaller the entropy value and the greater the weight of the indicator, and vice versa. The weight calculation steps using the entropy weight method are as follows:

Calculation of entropy value of evaluation indicators

Firstly, use standardization methods to standardize the obtained indicator data and obtain a judgment matrix R. Set the obtained evaluation matrix $R=(r_{ij})_{m\times n}$, where m refers to the number of evaluation indicators; n refers to the number of evaluation objects. Then the entropy value of the i-th evaluation index can be calculated using equation (4):

$$H(i)=-(1/\ln n)\sum r_{ij}\ln r_{ij} \qquad (4)$$

In the formula: $i=1,2,\ldots,m$, and specify when $r_{ij}=0$, $\ln r_{ij}=0$.

Calculation of entropy weight for evaluation indicators

Based on the entropy value, calculate the weight of the i-th indicator using equation (5) to obtain the weights of all indicators $V=(V_1,V_2,\ldots,V_m)$.

$$V_i=(1-H(i))\Big/\sum_{i=1}^{m}(1-H(i)) \qquad (5)$$

Combination weighting method

The combination weighting method comprehensively utilizes the advantages of subjective and objective weighting methods, effectively avoiding the shortcomings of subjective and objective weighting methods, and can more scientifically and reasonably obtain the weights of evaluation indicators [10]. The steps for calculating the comprehensive weight using the combination weighting method are as follows:

Calculation of subjective and objective weights

Firstly, the subjective weight and objective weight of the indicators are calculated using the extension analytic hierarchy process and entropy weight method, respectively. The subjective weight is assumed to be U_i, and the objective weight is assumed to be V_i;

Comprehensive weight calculation

Based on the weight calculation results of the extension analytic hierarchy process and entropy weight method, the combined indicator weight is calculated using equation (6) as follows:

$$\mathrm{W}_i=\frac{U_iV_i}{\sum_{i=1}^{m}U_iV_i} \qquad (6)$$

Grey whitening weight function clustering method

The grey whitening weight function clustering method can determine the membership relationship of certain evaluation indicators or objects to certain grey classes that have been divided. The typical types of grey whitening weight functions mainly include endpoint type triangular whitening weight functions and center point type whitening weight functions, and the evaluation results obtained by the center point type triangular whitening weight function clustering method will be more scientific and reasonable than those obtained by the endpoint type triangular whitening weight function clustering method [11]. Therefore, this article uses a center point type triangular whitening weight function to determine the evaluation level of driving behavior and various evaluation indicators. The specific evaluation process is as follows:

Firstly, based on the driving behavior evaluation index system, determine the evaluation objects and the number of evaluation indicators, and determine the number of gray categories and center points according to the evaluation level classification requirements. Therefore, it can be assumed that the number of evaluation objects, evaluation indicators, and grey categories are n, m, and s, respectively, and set λ_k as the center point of the k-th grey category. Therefore, the value range of grey category k is $[\lambda_{k-1}, \lambda_{k+1}]$, $k = 0,1,\ldots,s$ as shown in Figure 1.

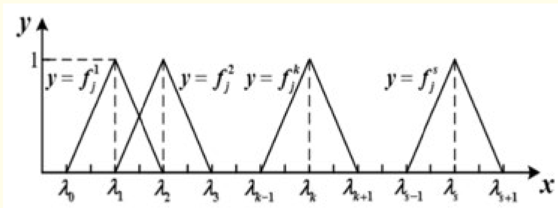

Figure 1: Schematic diagram of the triangle whitening weight function for the center point type.

Secondly, by connecting points $(\lambda_k, 1), (\lambda_{k-1}, 0)$ and $(\lambda_{k+1}, 0)$ obtaining triangular whitening weight functions between specific indicators *i* and grey class k, we can obtain triangular whitening weight functions between m indicators and s grey classes.

Assuming x_i is the actual data value of a specific indicator *i*, the degree of membership of the indicator with respect to grey class k can be determined by equation (7):

$$f_i^k(x)=\begin{cases} 0, x\notin[\lambda_{k-1},\lambda_{k+1}] \\ (x-\lambda_{k-1})/(\lambda_k-\lambda_{k-1}], x\in(\lambda_{k-1},\lambda_k] \\ (\lambda_{k+1}-x)/\lambda_{k+1}-\lambda_k, x\notin(\lambda_k,\lambda_{k+1}) \end{cases} \quad (7)$$

Furthermore, equation (7) can be used to obtain the membership vectors of specific evaluation index x_i for all *s* grey classes, set as $F_i = (f_i^1, f_i^2, \ldots f_i^s)$, $i = 1,2,\ldots,$ m. Similarly, based on the above method, the membership vectors of all evaluation indicators regarding s grey classes can be obtained, and the final membership matrix is formed as follows:

$$F=[F_1,F_2,\ldots,F_m]^T=\begin{bmatrix} f_1^1(x_1)f_2^1(x_2)\cdots f_m^1(x_m) \\ f_1^2(x_1)f_2^2(x_2)\cdots f_m^2(x_m) \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ f_1^s(x_1)f_2^s(x_2)\cdots f_m^s(x_m) \end{bmatrix}_{s\times m} \quad (8)$$

Fuzzy Comprehensive Evaluation Method

The fuzzy comprehensive evaluation method can transform qualitative evaluation problems that are difficult to quantify into quantitative evaluation problems through fuzzy mathematics, thus making the evaluation results more objective and specific. Specifically, by using equation (9) to perform fuzzy operations on the obtained membership matrix F and the comprehensive weight vector W of the indicators, the grey clustering evaluation vectors of all indicators are obtained:

$$Q^T = F \cdot W^T \quad (9)$$

In the formula: “$\bullet$” - fuzzy operator, using weighted average fuzzy operator $M(\bullet,\oplus)$.

Construction of a comprehensive evaluation model for driving behavior Methods

Introduction to Natural Driving Data

Natural driving data usually refers to the general term for data such as vehicle status, lane, geographic location, weather, etc. when a vehicle is in a normal driving state. There are various ways to obtain natural driving data, such as installing various sensors on the vehicle body to collect real-time vehicle status information and external environment information during the driving process. However, this data acquisition method has a high cost and has not been widely used in various car manufacturers' listed models. At present, the common method used in various types of vehicle models on the market is to obtain natural driving data through on-board OBD terminals. OBDII (the second on board diagnostics second generation) is a unified on-board diagnostic standard developed by the United States in 1994, used to detect input and output signals of vehicle control units and electronic circuits, and dynamically read vehicle information such as engine, water tank, exhaust emissions, and vehicle speed every 10 seconds on average [12]. In the driving behavior evaluation model, three data items, namely vehicle status information, geographic location information, and travel record information obtained from OBD, are mainly used to reflect the driving behavior of drivers.

After analyzing different types of information, this article selected some data items that can reflect driving behavior from the natural driving data analyzed as the data basis for evaluating driving behavior. As shown in Table 1.

Data item type	***Data item name***
Geographic location information	GPS speed
	GPS longitude
	GPS dimension
Travel Record Information	Collection time
	Average fuel consumption
	Longitudinal acceleration
	Lateral acceleration
	Speed
	Engine speed
	Engine water temperature
Vehicle status information	Left front tire pressure alarm
	Left rear tire pressure alarm
	Right front tire pressure alarm
	Right rear tire pressure alarm
	EPS fault indication
	ABS fault indication
	EPB
	Airbag indication
	Tire malfunction indication
	Transmission fault indication
	ESP system indication

Table 1: Data items required for driving behavior evaluation.

Research on Evaluation Indicators and Determination of Evaluation Indicator System

This article constructs a three-layer driving behavior evaluation index system that combines the target layer, criterion layer, and indicator layer. Among them, the target layer refers to the comprehensive evaluation of driving behavior, represented by *A*. By summarizing and summarizing the relevant content of the "Safety Operating Regulations for Motor Vehicle Drivers" issued by the Traffic Management Bureau of the Ministry of Public Security, this article will comprehensively evaluate driving behavior from four key dimensions: driving stability, operating regulations, vehicle health, and economic energy conservation. The driving stability dimension mainly concerns the driver's ability to control the vehicle's speed; The operation specification dimension focuses on whether the driver can operate the brake device, accelerator device, steering wheel and turn signal accurately and normatively during driving; The vehicle health dimension mainly focuses on the performance status of the vehicle, which is a comprehensive expression of the vehicle's fault characteristics and the driver's fault handling ability; The economic and energy-saving dimension comprehensively reflects the energy-saving and emission reduction qualities of a driver. Therefore, the criterion layer can be composed of four key dimensions of driving behavior evaluation, namely driving stability, operating standards, vehicle health, and economic energy efficiency, represented by B_1, B_2, B_3 and B_4 respectively.

In addition, to improve the accuracy of driving behavior evaluation, the monthly driving data of drivers is used as the analysis basis for driving behavior evaluation. According to the processed natural driving data, the data is classified into 11 categories as the indicator layer of the model, including the number of overspeed c_1, number of failed driving c_2, number of sharp turns c_3, number of sharp acceleration c_4, number of sharp deceleration c_5, average fuel consumption c_6, number of long idle c_7, number of speed mismatches c_8, number of engine high water temperature c_9, number of failures c_{10}, and number of engine high speeds c_{11}.

By conducting research on vehicle practitioners and driver users, each indicator is defined and selected based on the following criteria: (1) Rapid acceleration: When the vehicle is driving in different driving scenarios, the acceleration of the vehicle should be within a standard range. Sudden and violent tightening of the throttle can cause a sharp increase in the fuel injection and speed per unit time of the engine, resulting in an increase in fuel consumption and pollutant emissions at equal vehicle speeds. At the same time, it can also reduce the service life of components such as cylinder walls, pistons, etc [13]. Involving dimensions of vehicle health and economic energy conservation; (2) Rapid deceleration: There is often a positive correlation between rapid deceleration and rapid acceleration. This type of operation not only increases fuel consumption, pollutant emissions, and decays the lifespan of components, but also seriously affects driving safety. Therefore, rapid deceleration involves driving stability, operating standards, and economic and energy-saving dimensions; (3) Sharp turns: Sharp turns can easily cause traffic accidents such as vehicle rollovers, seriously affecting driving safety, involving driving stability and operational norms; (4) High engine speed: Excessive engine speed can cause a large amount of fuel to burn violently in a short period of time, leading to a violent increase in engine temperature. Maintaining high RPM driving for a long time can seriously damage the engine, involving the dimensions of vehicle health; (5) Average fuel consumption refers to the average fuel consumption of a driver driving $100km$. This indicator data can measure the economic energy-saving performance of driving behavior , involving the dimension of economic energy-saving; (6) Fault driving: Driving a vehicle in a faulty state can increase the risk of driving, so drivers should discover and solve the problem in the shortest possible time to avoid fault driving to the greatest extent possible;(7) Long idle speed: By referring to the "Operating Regulations for Energy Saving in Automotive Driving", it can be seen that when the vehicle is stationary, the driver should shut down the engine within 60 seconds for any purpose, reduce additional fuel consumption, and achieve the goal of energy conservation and emission reduction, which involves economic and energy-saving dimensions; (8) Overspeed: During the driving process of a vehicle, speeding is the direct cause of numerous accidents in various driving scenarios, involving the dimension of operational norms; (9) Speed mismatch: The mismatch between engine speed and vehicle speed can cause unstable torque output and insufficient fuel combustion, resulting in increased carbon deposition and affecting the engine's service life; (10) High engine water temperature: refers to the excessively high temperature of the engine coolant, which can seriously damage the vehicle's cooling system, making it impossible for various components of the engine to cool down and maintain high temperature conditions, thereby increasing the probability of engine damage, involving the dimensions of vehicle health; (11) Fault frequency: refers to the frequency of vehicle faults within a certain time or mileage, which comprehensively reflects the vehicle's performance and involves the dimensions of vehicle health. The overall evaluation system is composed of the above indicators, as shown in Figure 2.

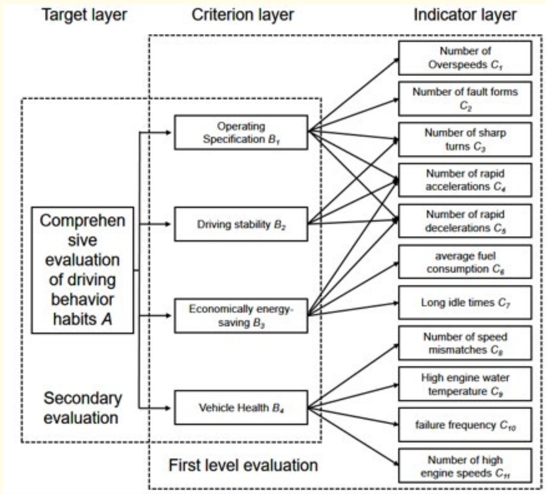

Figure 2: Comprehensive evaluation index system for driving behavior.

Determine the evaluation level comment set and whitening weight function

Based on the actual driving behavior of the driver and combined with expert experience, determine the evaluation set: $O = \{o_1, o_2, o_3, o_4, o_5\}$ = {very bad, bad, average, good, excellent}. The meanings of each level are shown in Table 2.

Evaluation level	***Corresponding whitening weight function***
very bad	[-0.1,0.125,0.35]
bad	[0.125,0.35,0.55]
average	[0.35,0.55,0.75]
good	[0.55,0.75,0.925]
excellent	[0.75,0.925,1.1]

Table 2: Rating and Whitening Weight Function of Driving Behavior Evaluation.

Dimensional evaluation of driving behavior standards layer

Acquisition of indicator layer indicator data

Firstly, the initial natural driving data is processed to obtain the data of the indicator layer. The main indicators include the need to further process the collected raw natural driving data to identify their corresponding behaviors or states, including the number of speeding, rapid acceleration, sharp turns, rapid deceleration, speed mismatch, and high engine speed.

Overspeed behavior recognition: Liu Yingji (2013) proposed a speed recognition algorithm based on satellite positioning data, which is more suitable for the existing situation in China and is also more accurate in recognition [14]. Based on obtaining speed data from natural driving data, the maximum speed limit for different geographies is set to overspeed threshold V_a. The geographical location of vehicles can be roughly divided into two categories: ordinary roads and highways. Therefore, the overspeed threshold V_a for ordinary roads is taken as $60\,km/h$, and the overspeed threshold V_a for highways is taken as $120\,km/h$. The number of speeding times is selected based on the geographical location of the trip, and the data items exceeding the threshold are accumulated to obtain the number of speeding times.

Rapid acceleration behavior recognition: Perezc A, Garcia M I, and Nieto M proposed a method for remotely monitoring the driving status of vehicles using acceleration sensors, which is suitable for processing the data collected in the article [15]. Through the analysis of relevant information and experimental data, it is found that during normal acceleration, the longitudinal acceleration of a car is generally maintained at 1m/s^2 to 2m/s^2. When the acceleration is between 2m/s^2 and 4m/s^2, it belongs to rapid acceleration. Therefore, this article selects a threshold of 3m/s^2 for acceleration based on industry experience, and accumulates the longitudinal acceleration values in natural driving data that exceed the threshold to obtain the number of rapid accelerations.

Rapid deceleration behavior recognition: Tesheng Hsiao proposed that in general, when the vehicle's acceleration value is less than -4m/s^2, the vehicle is mostly in a state of sudden braking, and the brake lights flash at a certain frequency. Here, this article sets the acceleration threshold for sudden deceleration to -4m/s^2, and then accumulates the longitudinal acceleration values in natural driving data that are less than the threshold to obtain the number of sudden decelerations.

Sharp turn behavior recognition: Currently, it is generally believed in the industry that ordinary sedans generally have corresponding normal speeds when driving in different curves, as shown in Table 3. In addition, the absolute value of lateral acceleration during normal cornering is generally not higher than 2m/s^2, so whether the vehicle is making a sharp turn is related to the magnitude of lateral acceleration. Accumulate the behavior of acceleration exceeding the threshold during turning.

High speed recognition: From the engine speed data obtained from the OBD device terminal in this article, it can be seen that the speed of most vehicles is maintained between 1000 and 2500 revolutions, with some but very few exceeding 2500. Based on industry experience and relevant research, the threshold for high engine speed is selected as 2500 revolutions, and the data of engine speed exceeding 2500 revolutions is accumulated to obtain the number of high engine speeds.

Speed mismatch recognition: Based on the preliminary processing results of data obtained from the OBD device terminal, it was found that due to the different cardinalities of engine speed and vehicle speed changes. Liu Kaili proposed to calculate the relative ratio of vehicle speed to engine speed [6], and the algorithm formula is as follows:

$$R(t) = \frac{V_t}{220} \div \frac{n_t}{8000}$$

Based on this calculation formula, it is generally believed that when $R(t)$ is between 0.8 and 1.3, the speed and vehicle speed match each other. Therefore, the judgment threshold for speed mismatch can be set as:

$$R(t)<0.8 \text{ or } R(t)>1.3$$

Accumulate the number of times the engine speed does not match the natural driving data that exceeds the threshold.

Design speed (km/h)	***40***	***30***	***20***
Horizontal curve radius	<125	<60	<30

Table 3: Division of Sharp Turn Horizontal Curve Radii in Road Sections.

Data preprocessing

According to the evaluation requirements, collect relevant data on m underlying indicators of the object to be evaluated, and perform dimensionless processing to form a standardized sample matrix. The specific methods are as follows:

For the larger the better indicator x_{ij}, make:

$$y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad (10)$$

For the smaller the better indicator x_{ij}, make:

$$y_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{11}$$

For indicator x_{ij} that is closer to x_i and better, make:

$$y_{ij} = 1 - \frac{x_{ij} - x_i}{\left|\max(x_{ij}) - x_i\right|} \tag{12}$$

In equation (10) ~ (12) $i = 1, 2, \ldots, m,\ j = 1, 2,$;

Calculate the comprehensive weight of underlying indicators

Determine the subjective and objective weights of each indicator using the two types of subjective and objective weight calculation methods proposed in this article, and then calculate the comprehensive weights through the combination weighting method. The subjective weight $U_1 = (u_1, u_2, \ldots, u_m)$ of the underlying indicators can be obtained by using equations (1) to (3), the objective weight $V_1 = (v_1, v_2, \ldots, v_m)$ can be obtained by using equations (4) to (5), and the comprehensive weight $W_1 = (w_1, w_2, \ldots, w_m)$ can be obtained by using equations (6).

Grey clustering evaluation of underlying indicators

Substitute the values of the underlying indicators into equations (10) to (12) of the whitening weight function to obtain the compliance matrix *F* of each underlying indicator with respect to *s* gray classes. Furthermore, using (9) combined with the comprehensive weight W_1 and the compliance matrix *F*, calculate the grey class evaluation vector calculation results of the underlying indicator:

$$Q^T = (q_1, q_2, \ldots, q_s)^T$$

Comprehensive evaluation of user driving behavior

Building a Level 2 Driving Behavior Evaluation Matrix

Through step 3 of section 3.3, the grey evaluation vector Q corresponding to all underlying indicators can be obtained to construct a second level driving behavior evaluation matrix:

$$A = [Q_1^T, Q_2^T, \cdots, Q_m^T] = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1s} \\ q_{21} & q_{22} & \cdots & q_{2s} \\ \cdots & \cdots & & \cdots \\ q_{m1} & q_{m2} & \cdots & q_{ms} \end{bmatrix}_{m \times s} \tag{13}$$

In the formula: m - the number of indicators (i.e. key indicators for driving behavior evaluation) in the criterion layer; S - Number of grey classes.

Calculate the comprehensive weight of the criterion layer

Use equations (1) to (3) to calculate the subjective weight of $U_2 = (u_1, u_2, \cdots, u_m)$ the criterion layer indicators. Use equations (4) to (5) to obtain an objective weight of $V_2 = (v_1, v_2, \cdots, v_m)$, and (6) to calculate the comprehensive weight of the criterion layer as $W_2 = (w_1, w_2, \cdots, w_m)$.

Fuzzy comprehensive evaluation of user driving behavior of drivers

By using the fuzzy comprehensive evaluation method, the comprehensive evaluation vector of the driver's driving behavior can be obtained:

$$B = W_2 \cdot A = [w_1, w_2, \cdots, w_m] \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1s} \\ q_{21} & q_{22} & \cdots & q_{2s} \\ \cdots & \cdots & & \cdots \\ q_{m1} & q_{m2} & \cdots & q_{ms} \end{bmatrix} = (b_1, b_2, \cdots, b_s) \tag{14}$$

According to the principle of maximum membership, the driving behavior of the driver can be determined. The driver's driving behavior evaluation process is shown in Figure 3.

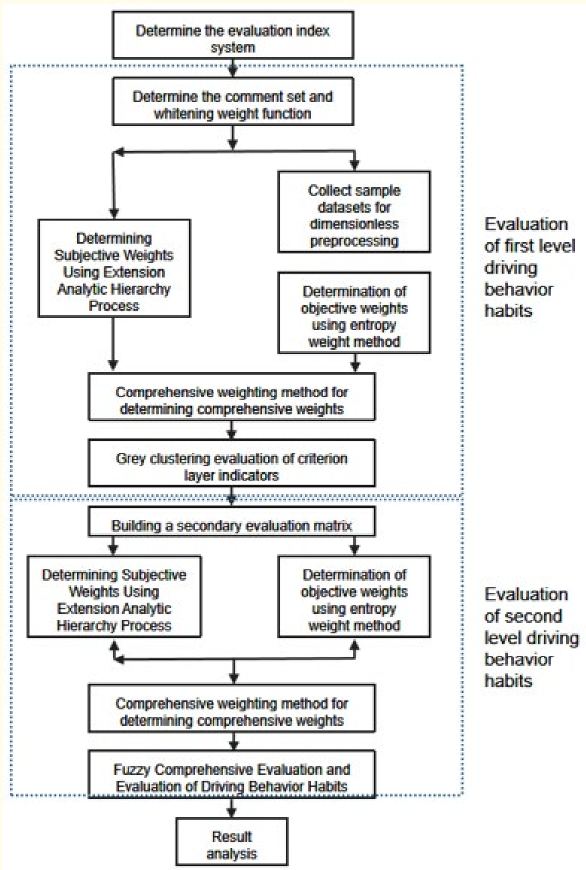

Figure 3: Comprehensive Evaluation Flow Chart of Driving Behavior.

Results & Discussion

Index data acquisition and preprocessing

Based on the natural driving data collected by the OBD device of a certain vehicle for three months, first use the identification method of relevant indicators in Section 3.4 to obtain the data of each indicator layer, and then use equations (10) to (12) to perform dimensionless processing on the original data. The results are shown in Table 4.

Index	*January*	*February*	*March*
Number of rapid accelerations	0.9398	0.9195	0.9002
Number of rapid decelerations	0.9401	0.9512	0.9518
Average fuel consumption	0.9914	0.9188	0.9279
Long idle times	0.8892	0.8397	0.8105

Table 4: Dimensionless Data of Relevant Indicators for Economic Energy Conservation.

Dimensional evaluation of driving behavior standards layer

Calculation of comprehensive weight of indicator layer

Construct a dimensionless matrix on the dimensions of economic energy conservation based on Table 4

$$Y = \begin{bmatrix} 0.9398 & 0.9195 & 0.9002 \\ 0.9401 & 0.9512 & 0.9518 \\ 0.9914 & 0.9188 & 0.9279 \\ 0.8892 & 0.8397 & 0.8105 \end{bmatrix}$$

According to equation (5), the entropy vector can be obtained as:

$$H_{B3} = (-0.6693, 0.1511, 0.2308, 0.3897)$$

According to (6), its corresponding entropy weight vector can be determined as:

$$V_{B3} = (0.4175, 0.2202, 0.1965, 0.1658)$$

Hire two experts to compare and score the relevant indicators of economic energy conservation in pairs, as shown in Tables 5 and 6.

B_3	c_4	c_5	c_6	c_7
c_4	<1,1>	<1.4,2.7>	<2.3,3.1>	<3.5,4.6>
c_5	<0.37,0.71>	<1,1>	<1.9,2.9>	<1.3,2.2>
c_6	<0.32,0.43>	<0.34,0.53>	<1,1>	<1.8,2.8>
c_7	<0.22,0.29>	<0.45,0.77>	<0.36,0.56>	<1,1>

Table 5: Expert 1’s Scoring Data on Economic Energy Conservation Dimension Indicators.

B_3	c_4	c_5	c_6	c_7
c_4	<1,1>	<2.2,3.4>	<2.7,3.6>	<2.7,3.3>
c_5	<0.29,0.45>	<1,1>	<1.2,2.6>	<2.3,3.2>
c_6	<0.28,0.37>	<0.28,0.83>	<1,1>	<2.4,3.6>
c_7	<0.30,0.37>	<0.31,0.43>	<0.28,0.42>	<1,1>

Table 6: Expert 2's Scalable Interval Number Scoring Data for Economic Energy Conservation Dimension Indicators.

Using equations (1) to (3), the weight vector can be obtained:

$$U_{B3} = (0.5567, 0.2197, 0.1806, 0.0430)$$

According to equation (6), the comprehensive weight vector is:

$$W_{B3} = (0.7175, 0.1512, 0.1107, 0.0206)$$

Grey clustering evaluation of underlying indicators

$$F = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1994 & 0.1813 \\ 0.8872 & 0.9558 & 0.8006 & 0.8187 \end{bmatrix}$$

Evaluation of economic and energy-saving dimensions

By substituting the obtained comprehensive weight vector W_{B3}, the conformity matrix *F*, into equation (9), the comprehensive evaluation vector $Q_{B3} = (0, 0, 0, 0.0295, 0.8531)$ can be obtained. According to the principle of maximum membership, the rating of the economic energy-saving dimension is in a good level in this case. By using the same method, the rating level vectors for all criteria dimensions of driving behavior can be obtained, as shown in Table 7.

Evaluation level	***Very bad***	***Bad***	***Average***	***Average***	***Excellent***	***Result***
Operating specifications	0	0	0.0706	0.4429	0.5672	excellent
Driving stability	0	0	0.0517	0.3092	0.6448	excellent
Economic and energy-saving	0	0	0	0.0295	0.8531	excellent
Vehicle Health	0	0.0109	0.1921	0.5826	0.4021	excellent

Table 7: Comprehensive evaluation results of driving behavior criteria layer.

Comprehensive evaluation of the target layer

Construct the second level evaluation matrix A based on the comprehensive evaluation results of the first level indicators:

$$A=\begin{bmatrix}0 & 0 & 0.0706 & 0.4429 & 0.5672\\ 0 & 0 & 0.05174 & 0.3092 & 0.6448\\ 0 & 0 & 0 & 0.0295 & 0.8531\\ 0 & 0.0109 & 0.1921 & 0.5826 & 0.4021\end{bmatrix}$$

According to equation (4), the entropy vector can be obtained as:

$$H_2=(0.4198, 0.5023, 0.1325, 0.6182)$$

According to equation (5), the corresponding entropy weight vector is:

$$V_2=(0.2396, 0.2116, 0.3709, 0.1779)$$

Hire two experts to rate the importance of operating standards, driving stability, economic energy conservation, and vehicle health, and use the extension analytic hierarchy process to obtain the weight vector:

$$U_2=(0.2915, 0.1706, 0.4698, 0.0681)$$

According to equation (6), the comprehensive weight vector is:

$$W_2=(0.2411, 0.1256, 0.6021, 0.0312)$$

Using equation (14), the final comprehensive evaluation vector can be obtained as

$$B=(0, 0.0006, 0.0286, 0.2104, 0.7604)$$

According to the principle of maximum membership, the driver's driving behavior is at an excellent level, completing a comprehensive evaluation of driving behavior.

Conclusion

This article proposes a comprehensive evaluation method for driving behavior. Firstly, the key evaluation dimensions and related indicators that affect driving behavior are layered, and then the key components are evaluated at the first level using grey clustering method to obtain the evaluation levels of the key evaluation dimensions for each driving behavior evaluation; On this basis, the second level evaluation of driving behavior is conducted using the fuzzy comprehensive evaluation method, and the final level evaluation result of the entire driving behavior is obtained. In addition, in terms of weight determination, the extension analytic hierarchy process and entropy weight method are first used to calculate the subjective and objective weights of each indicator, and based on this, the comprehensive weights of the indicators are calculated using the combination weighting method, thus compensating for the shortcomings of the single weighting method in weight determination and providing a new means for determining indicator weights, which has good practical value.

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