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Study on the Impact Degrees of Several Driving Behaviors When Driving While Performing Secondary Tasks

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ABSTRACT Driving while performing secondary tasks is a common phenomenon and can lead to car crashes and human injuries. However, the impact degrees of several secondary tasks have not been determined. To study the importance of several secondary task driving behaviors on driving safety, an eye movement tracking system and a vehicle running state collection system were utilized to determine the laws of behavioral parameters when driving while performing six secondary tasks including Bluetooth calls, cell phone calls, sending text messages, operating car-mounted players, chatting, and singing. Then, an experiment was carried out to collect the evaluation indices of eye movement behaviors and vehicle running statuses. A characteristic extraction method that is based on the gray incidence clustering method was used to extract the characteristic evaluation indices. The generalized gray Euclidean distance was utilized to extract the characteristic evaluation indices. Then, seven characteristic evaluation indices were extracted from 17 evaluation indices. In order to verify the accuracy of the evaluation index system, 17 candidate evaluation indices were screened out to eight by principal component analysis. From this result, the established evaluation index system is all included in eight indices selected by principal component analysis. Furthermore, the characteristic evaluation indices and the six secondary task modes were combined to build the entropy weight decision-making matrix, based on which the weights of each driving behavior mode were determined via the entropy weight method and the impact degrees of the six driving behavior modes on the driving safety were obtained. The results of this research demonstrate that the operation of car-mounted players had the greatest impact on driving safety, whereas making cell phone calls had the least impact.

INDEX TERMS Driving safety, entropy weight method, gray incidence clustering method, secondary task mode.

I. INTRODUCTION

With the rapid development of electronic devices, more cars are being equipped with devices such as vehicle navigation systems and in-vehicle music players. In addition, although the use of cell phones while driving is illegal in many countries, this phenomenon is still widely encountered. In the scenario of driving while performing multiple tasks, the task that keeps the car driving safely is defined as the ''primary task''. In contrast, tasks that may distract the driver are generally named ''secondary tasks'', such as using cell phones, chatting, and manipulating vehicle navigation systems.

When driving while performing multiple tasks, the driver's attention is divided among the primary task and secondary tasks. This results in potential risks and injuries.

According to a survey of national highway traffic safety administration (NHTSA) [1], in 2015, 3477 people were killed and 391,000 were injured in motor vehicle crashes from which the cause can be attributed to the distraction of drivers. During daylight hours, approximately 660,000 drivers are using cell phones when driving. That creates enormous potential for deaths and injuries on U.S. roads.

From the "Driver Electronic Device Use in 2015" investigation by NHTSA, the percentage of passenger vehicle drivers that are text-messaging or visibly manipulating handheld devices remained constant at 2.2 percent in 2015. Driver handheld cell phone use decreased from 4.3 percent in 2014 to 3.8 percent in 2015; this was not a statistically significant decrease.

Detection of the influence degrees of secondary tasks could be used in usage-based insurance (UBI) and onboard diagnostics (OBD). Thus, it is significant to study the influence degrees when driving while performing secondary tasks. Because of the rapid development of electronic equipment and the increasing diversity of intellectual products, secondary-task driving behavior modes, which affect the driver's safety, could no longer be ignored, such as taking Bluetooth calls and sending text messages. The secondary tasks distract drivers from focusing on the road ahead, interrupt the gaze on the road and increase cognitive burden [2]. Sun *et al.* [3] selected three design indices to study the dynamic responses and the stability of piecewise linear systems for suspension mechanisms. And they proved that the stability of the steady-state motion was determined by the three indices. Hybrid genetic algorithm (GA) was used to optimize the key indices to calculate and predict tyre-road friction force [4].Through the driving behavior of the driver obtained from the big data platform, Xiong *et al.* [5] analyzed how the automobile braking force matches with driving behaviors. Zheng *et al.* [6] proposed an expectation maximum algorithm to classify the measured eye-gaze points, furthermore, they indicated that the small-size display will bring on significantly longer glance time that may results in the increasing of visual distraction for drivers. Driving fatigue affects the reaction ability of a driver, such as electroencephalograph (EEG) and mental states [7]. According to the data analysis of a study on 100 adult drivers [8], when the gaze leaves the road ahead for more than two seconds, the accident risk doubles. Furthermore, a previous study [9] shows that mobile phone calls and text messages could increase the response time of drivers to various road conflicts, whereas text messaging is more serious. Therefore, it is necessary to study the safety issues of performing secondary tasks while driving.

Compared with driving while performing primary tasks, driving while performing several secondary tasks at the same time had a substantial negative impact on driving safety [10]. People's reaction times with phone calls were typically 20% longer than without phone calls [11]. Driving safety was related to the performance of multiple tasks and visual information processing in several acceleration scenarios [12]. The safety evaluation model of secondary-task driving was established by using the Fuzzy Analytical Network Process (F-ANP), which provided a reference for the analysis and risk prevention of secondary-task driving safety [13]. The association between eye glance duration and crash risk with novice teenage drivers has been established [14] and the result demonstrated that the longer the eyes glance off the road, the greater the risk.

As better performing conventional statistical models, gray system models require only a limited amount of data to estimate the behavior of unknown systems [15]. The main principle of gray incidence analysis [16] is to calculate the gray incidence degrees. The gray incidence sequence was used to describe the relationship between the driving behavior modes and the evaluation indices. The gray incidence clustering method [17] is a method for dividing objects into several categories according to the gray incidence matrix.

The entropy weight method is an objective weighting method. In AHP, ANP and other weighting methods, there is no man-made decision step that is similar to 'expert evaluation' in the entropy weight method. This conforms with the principle. Hence, no changes are made to the original data. Then, regulations are identified from the original data. The entropy weight method is an objective weighting method that can analyze and measure the amount of information in the data of secondary task modes and avoid subjective factors. Therefore, the weights of each driving behavior mode can be determined objectively, which makes the evaluation results more objective.

In this paper, the gray incidence clustering method was used to classify the evaluation indices [18] and the generalized gray Euclidean distance [19] was used to extract the characteristic evaluation indices. The decision-making matrices of the evaluation indices and driving behavior modes were constructed and the weights of each mode were determined by the entropy weight method. Each weight value [20] represents the impact of a secondary-task driving behavior mode on driving safety.

II. METHOD OF SELECTING THE CHARACTERISTIC EVALUATION INDICES

A. EVALUATION INDICES OF SECONDARY TASK MODES

In the field of driving behavior research, the analysis of drivers' behavior indices mainly includes lateral vehicle operation parameters and longitudinal vehicle operation parameters such as steering wheel, steering light, brake pedal and accelerator pedal etc.. The longitudinal operation indices of input quantity such as vehicle speed, trajectory and lateral acceleration. Leff *et al.* [21] found that multi-task can affect driving behavior and reduce the ability of controlling vehicles, such as increasing the number of emergency brakes and the standard deviation of steering angle. When driver carries out different difficulty processes, the vehicle trajectory, speed, longitudinal and lateral acceleration and other vehicle operating parameters have changed significantly [22], [23]. Barkana *et al.* [24] found that the standard deviation of car speed during driving is larger than that of normal driving. Takei *et al.* [25] established a driver fatigue detection system through steering wheel angle, grip force, and used the results of fatigue degree to evaluate driving safety [25]. Scholars from Nottingham University established an accident research laboratory and study the influence of different psychological

TABLE 1. Evaluation indices with English abbreviations.

No.	Category	Abbreviation	Meaning of evaluation index
1	Eye movement status	M-SC	Mean Saccadic Velocity
2		SD-SV	Standard Deviation of Saccadic Velocity
3		M-BF	Mean Blink Frequency
4		SD-BF	Standard Deviation of Blink Frequency
5		PSV	Peak Saccadic Velocity
6		SD-PSV	Standard Deviation of Peak Saccadic Velocity
7		M-BD	Mean Blink Duration
8		SD-BD	Standard Deviation of Blink Duration
9	Vehicle running status	M-TOV	Mean Throttle Opening Value
10		SD-TOV	Standard Deviation of Throttle Opening Value
11		M-SWA	Mean Steering Wheel Angle
12		SD-SWA	Standard Deviation of Steering Wheel Angle
13		SD-VA	Standard Deviation of Vertical Acceleration
14		M-LV	Mean Longitudinal Velocity
15		SD-LV	Standard Deviation of Longitudinal Velocity
16		M-LAV	Mean Lateral Acceleration Value
17		SD-LAV	Standard Deviation of Lateral Acceleration Value

loads on driving skills by analyzing driver's eye movement indices [26]. Furthermore, relevant stability control evaluation indices were utilized to provide good handling and reduce the driver's fatigue effectively [27].

Based on the previous studies in this field, as many indices as possible that could reflect the distraction of drivers are selected. After dimensionality reduction of the indices, the indices that are able to reflect the characteristics of the complete set of indices are called "characteristic evaluation indices" in this paper. In the stage of computing the impact degrees of secondary task modes, fewer variables could simplify subsequent calculations and reduce the calculation errors.

The indices were chosen based on measurements from our experimental platform, an eye tracking device and a vehicle state observation device. The principle of selecting indices is divided into two parts: references of other scholars' research and a summary of our former investigating results.

1) STEERING WHEEL ANGLE

The control precision of the steering wheel by the driver decreases when the distractibility increases. Two characteristics of steering wheel performance are evident when drivers perform a normal driving task: large correction of low frequency and large adjustment at a rapid rate after holding on for a long time.

2) EYE MOVEMENT STATUS

The blink frequency changes when drivers are tired. Hence, when exploring secondary-task driving in our research, the reference category of "blink" will be used as evaluation indices.

3) VELOCITY

Fatigue levels are reflected by the driver's ability to control the velocity. Driver distraction, the average speed and the standard deviation of the speed reflect the driver's ability to control the speed.

In the next stage of the study, these evaluation indices will be used to establish secondary-task driving safety evaluation model. According to the weight of each index, the model will allocate the corresponding influence degree to them to reflect behavioral change of driver better. The selected evaluation indices are listed in Table 1.

B. GRAY SYSTEM THEORY

Gray system theory [28] is used to measure the relevance between two sequences, which is a relevance measure between objects and factors. The basic principle of gray incidence analysis can be described as follows. According to the comparison of the similarity degrees [29] of the statistical sequence curve geometry, the degree of incidence among the multiple evaluation indices in the system is determined. The closer the geometries of the sequence curves, the greater their degree of incidence. The evaluation indices that have a small incidence coefficient should be selected as the characteristic evaluation indices, which have strong independence and well reflect the features [30].

Before establishing the gray system, it is necessary to check the feasibility of the system by calculating the stepwise ratio of the time series $S = \{s(1), s(2), \cdots, s(n)\}$ [31]. The method of calculating the quasi smooth series $\rho(k)$ and the quasi exponential series $\sigma(k)$ of the sequence via (1). If and only if the condition is satisfied, the sequence data can be used in the gray system. Otherwise, the data need to be transformed properly to make the stepwise ratio, till the requirements are met. Taking one of the driver's evaluation index data as example randomly, Table 2 shows the results of $\rho(k)$ and $\sigma(k)$.

$$\begin{cases} e^{-\frac{2}{n+1}} \le \sigma(k) = \dfrac{s(k-1)}{s(k)} \le e^{\frac{2}{n+1}}, & k=1,2,\cdots n \\ 1 \le \rho(k) = \dfrac{s(k)}{s(k-1)} \le 1.5, & k=4,5,\cdots,n \end{cases} \tag{1}$$

TABLE 2. **Quasi smooth series and quasi exponential series of one driver's evaluation index.**

k	$\rho(k)$	$\sigma(k)$
1	1.7544	3.3412
2	1.1591	3.0191
3	1.0245	2.7567
4	0.8285	2.3825
5	0.6487	2.1244
6	0.5313	1.7542
7	0.4514	1.6561
8	0.3284	1.4804
9	0.3072	1.3002
10	0.2246	1.1446
11	0.2084	1.1204
12	0.1761	0.9171
13	0.1510	0.8750
14	0.1317	0.8168
15	0.1209	0.7990

As can be shown in Table 2, when k > 8, $\rho(k)$ and $\sigma(k)$ meet gray correlation conditions. So the data set of indices is able to construct gray correlation system.

C. DENG'S GRAY INCIDENCE DEGREE

Suppose N is the number of evaluation indices in a driving behavior mode, and all evaluation indices are denoted as $X_1, X_2, \cdots, X_n$. The normalized data that are measured for each evaluation index in various driving behavior modes are $x_i(k)$, $(i = 1, 2, \cdots, n; k = 1, 2, \cdots, m)$, and the index sequence is $X_i = (x_i(1), x_i(2), \cdots, x_i(m))$.

For a specified driving behavior mode, Deng's gray incidence coefficient that corresponds to evaluation index i and evaluation index j is γ_{ij}, which is defined in (2).

$$\begin{aligned} \Delta_{\min}(k) &= \min\min |x_i(k) - x_j(k)| \\ \Delta_{\max}(k) &= \max\max |x_i(k) - x_j(k)| \\ \gamma_{ij}(k) &= \frac{\Delta_{\min}(k) + \rho \cdot \Delta_{\max}(k)}{|x_i(k) - x_j(k)| + \rho \cdot \Delta_{\max}(k)} \end{aligned} \tag{2}$$

where $\rho \in (0, \infty)$ is the distinguishing coefficient. The smaller ρ is, the greater the resolution is; typically, 0.5 is considered an optimal value [32].

Deng's gray incidence degree is obtained by averaging the weights, as expressed in (3).

$$r_{ij} = \frac{1}{m}\sum_{k=1}^{m} \gamma_{ij}(k) \tag{3}$$

The incidence degree r_{ij} reflects the relevance of evaluation indices X_i and X_j. After the above calculation, the incidence degree sequence between evaluation index X_i and other evaluation indices are obtained as expressed in (4).

$$r_i = (r_{i1}, r_{i2}, \cdots, r_{in}) \tag{4}$$

The incidence degree sequences of the evaluation indices are arranged to form Deng's incidence matrix, as expressed in (6).

$$R = \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ r_4 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix} \tag{5}$$

D. GRAY INCIDENCE CLUSTERING METHOD

The incidence matrix R consists of n evaluation indices [33], [34] and the generalized gray Euclidean distance of dynamic clustering is obtained via Deng's gray incidence degree [35]. The generalized gray Euclidean distance d_i between evaluation index X_i and cluster center m_k is defined in (6).

$$d_i = d(X_i, m_k) = \left| \frac{1}{\sum_{j=1}^{n} r_{ij}} - m_k \right| \tag{6}$$

The number of cluster samples is k. The steps of the gray cluster incidence analysis algorithm are as follows:

1) For a specified driving behavior mode, an evaluation index is selected as cluster center m_1 randomly. Then, the distances between the other n-1 evaluation indices and m_1 are calculated via (6). The evaluation index that corresponds to the maximum distance is selected as the second cluster center, which is denoted as m_2.

2) The distances between the remaining n-2 evaluation indices and m_1 and m_2 are calculated. The evaluation index that has the max sum distance from m_1 and m_2 is selected as the third cluster center, which is denoted as m_3.

3) Cluster center m_i, which is farthest from all the other cluster centers, is regarded as the next cluster center. In the same manner, the calculation is continued until the number of clusters reaches k. Then, there are k cluster centers in total.

4) All other evaluation indices are classified into the categories of the nearest cluster centers to achieve the clustering of evaluation indices.

5) In each category of the evaluation indices, R_i is calculated and the index that corresponds to the largest R_i in each category is selected as the characteristic evaluation index.

$$R_i = \sum\nolimits_{j=1}^{n} r_{ij} \tag{7}$$

6) The above steps are repeated until the characteristic evaluation index of each category has been selected.

E. PRINCIPAL COMPONENT ANALYSIS

PCA (principal component analysis) can be used to reduce the dimension of data, and the uncorrelated principal components are defined as characteristic evaluation indices [36]. The characteristic evaluation indices system, which can retain most of the information provided by the original indices, can simplify the later calculation [37].

In this paper, to verify the reliability of the characteristic evaluation indices system established by gray system, PCA was utilized to screen the candidate evaluation indices. If the result is as same as gray system, the indices system is reasonable. The calculation steps of the PCA are as follows:

1) DATA STANDARDIZATION

The purpose of data standardization is to eliminate the incompatibility caused by data and dimensions, so the data need to be standardized in advance. There are n sample units and each of them has p evaluation indices. Then there is a matrix $X = (x_{ij})_{n\times p}$, where x_{ij} is the j-th index of the i-th sample. The matrix X is shown below:

$$X = (X_1, X_2, \cdots, X_p) = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}$$

The Z-score method is used to normalize the data via (8).

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{\sigma_{x_j}}, \quad (i \neq j, i, j = 1, 2, \cdots p) \tag{8}$$

$$\bar{x}_j = \frac{\sum_{j=1}^{n} x_{ij}}{n} \tag{9}$$

$$\sigma_{x_j} = \sqrt{\frac{\sum_{j=1}^{n} (x_{ij} - \bar{x}_j)^2}{n-1}} \tag{10}$$

In (8): where $\bar{x}_j$ is the arithmetic mean of X_j, σ_{x_j} is the standard deviation of, $Z = (Z_1, Z_2, \cdots, Z_p) = (z_{ij})_{n\times p}$ is the matrix after the data standardization.

2) CALCULATION OF EIGENVALUES AND EIGENVECTORS

The correlation coefficients between each two variables in the normalized matrix Z is calculated via (11).

$$r_{ij} = \frac{1}{n-1} \sum_{k=1}^{n} z_{ik} z_{kj} \quad (i, j = 1, 2, \cdots, p) \tag{11}$$

The correlation coefficient matrix R is:

$$R_{p\times p} = \sum = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{bmatrix}$$

According to the characteristic equation via (12) of the correlation coefficient matrix R, we can get p characteristic roots $\lambda_k, (k = 1, 2, \cdots, p)$ of matrix R.

$$|R - \lambda_k I| = 0 \tag{12}$$

Based on the characteristic polynomial $RU_j = \lambda_k U_j$, the corresponding eigenvector is $U_j = (u_{j1}, u_{j2}, \cdots, u_{jp})$.

3) OBTAINING THE PRINCIPAL COMPONENTS

PCA turns the initial variables into a small number of integrated variables by means of a variable transformation method. Furthermore, these few integrated variables also retain as much of the original data information as possible, thus the workload of the later analysis can be reduced.

The variance contribution rate is the proportion of the total variation caused by a single common factor, indicating the influence of this common factor on the dependent variables. The greater the variance contribution rate v_k, the greater the influence of the principal component variable $X_i(i - 1, 2, \cdots, p)$.

Cumulative variance contribution rate is the proportion of total variance caused by all common factors. It both can represent the influence of all common factors on the dependent variables and measure the importance of each index. The greater the variance contribution rate w_k is, the more information is contained in the former p principal components.

The variance contribution rate of the k-th principal component is:

$$v_k = \frac{\lambda_k}{\sum_{i=1}^{k} \lambda_i} \tag{13}$$

The cumulative variance contribution rate of the k-th principal component is:

$$w_k = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{p} \lambda_i} \tag{14}$$

The actual situation shows that the threshold of the cumulative variance contribution rate is set at $80\% \sim 85\%$ [38], which can ensure that the number of principal components is fewer when the information is sufficient enough, so that the evaluation results have a certain stability.

The cumulative variance contribution rate of more than 85% variance of the former q principal components contain the vast majority of the original information, mark as $\eta_i(i = 1, 2, \cdots, q)$, then the other principal components left behind can be discarded. The first principal component η_1 contains the most information of the original indexes, which is independent on other components. The second principal component η_2 is the one with the largest variance except η_1 and is independent on the other principal components. In this way, the resulting set of principal components is a simplified characteristic evaluation index system.

III. CALCULATION OF ENTROPY WEIGHTS FOR CHARACTERISTIC EVALUATION INDICES OF SECONDARY TASK MODES

A. ENTROPY WEIGHT METHOD

The entropy weight method is an objective and comprehensive weighting method [39]. Based on the variation degree of each secondary task mode, the entropy weight of each secondary task mode is calculated and the objective weights can be obtained by using entropy weights to modify the old ones [40]. The smaller the information entropy weight of a mode is, the more information it can provide and the more weight it will have.

B. CALCULATION OF OBJECTIVE WEIGHT BASED ON ENTROPY WEIGHT METHOD

When the entropy weight method is used to calculate the weight values, the data of the characteristic evaluation indices for each secondary task mode must be non-dimensionalized. As the entropy weight method must retain the differences among the original data, various methods are not suitable, including the extremal method $X_{ij} = \frac{x_{ij}}{\max - \min}$ and the standardization method $X_{ij} = \frac{x_{ij} - \bar{X}}{\sigma}$, which can make the entropy weight method unavailable or eliminate data discrepancies [41]. Thus, non-dimensionalization is performed via (15). This method can eliminate the influence of dimension and order of magnitude, whereas the information on the differences between the index values can be retained effectively. The greater the degree of difference, the greater the impact on the comprehensive analysis. The calculation steps of the entropy weight method are as follows:

1) Suppose there are n types of secondary task modes and m characteristic evaluation indices are extracted by the gray incidence clustering method based on these data. The decision-making matrix $X = (x_{ij})_{m \times n}$, which is composed of m rows and n columns, is obtained.

$$y_{ij} = \frac{x_{ij}}{\sqrt{x_j}} \quad (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n) \tag{15}$$

In (15), y_{ij} is the non-dimensional value of the j-th secondary task mode in the i-th characteristic evaluation index. Then, the normalization matrix is obtained.

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}, \quad 1 \le i \le m, \ 1 \le j \le n \tag{16}$$

2) The entropy weight h_j of the j-th secondary task mode is calculated by (17) and k is a constant that is related to m such that $k = (\ln m)^{-1}$, $k > 0$, and $h > 0$.

$$h_j = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij}, \quad 1 \le j \le n \tag{17}$$

3) The coefficient of variation for a secondary task mode is $1 - h_j$ and the weight vector of the secondary task mode is obtained by the entropy weight method as $\beta = (\beta_1, \beta_2, \cdots, \beta_n)$, with $n \in N^+$.

$$\beta_j = \frac{1 - h_j}{\sum_{j=1}^{n} (1 - h_j)}, \quad 1 \le j \le n \tag{18}$$

IV. EXPERIMENTAL SYSTEM AND METHODS

A. EXPERIMENTAL POPULATION

A total of 40 drivers (Male: 27, Female: 13) with a valid driving license were recruited. They were between the ages of 20 and 49 years (Mean = 29 years) and had been driving for 2 to 13 years (Mean = 5 years). This is the demographic that uses mobile phones and Bluetooth devices most actively.

TABLE 3. Distribution and proportions of driver age.

Age	Male	Female	Total	Percentage
20 to 25	10	6	16	40.0%
26 to 30	7	4	11	27.5%
31 to 35	7	3	10	25.0%
36 to 40	3	0	3	7.5%

FIGURE 1. Vehicle running status collection devices.

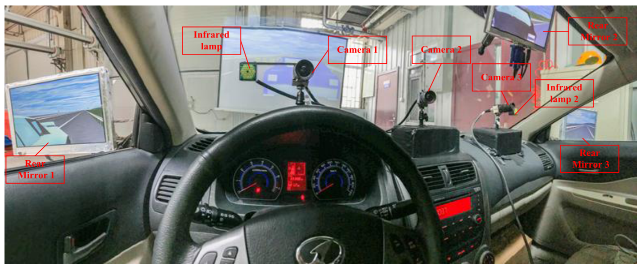

FIGURE 2. Eye movement tracking devices.

B. EXPERIMENTAL PLATFORM

The experiment platform consists of a vehicle running status collection system and an eye movement tracking system.

1) DRIVING SIMULATOR AND VEHICLE RUNNING STATUS COLLECTION SYSTEM

Taking an FAW car (Model: B70) as the main body, we transformed it into a driving simulator with a multiple-degree-of-freedom vehicle model that contains all driving control functions. A driving simulation software (Multigen Creator, Presagis, United States) was implanted for collecting the vehicle running statuses. The driving simulator can obtain the running states of vehicle units such as the engine, suspension, brakes, and clutch. Then, the characteristic parameters of the vehicle can be directly extracted from CAN Bus data, without depending on other sensors, which improves the real-time performance and robustness. The driving scene was set the Jilin City highway section to Changchun City highway section, as shown in Fig. 1.

2) EYE MOVEMENT TRACKING SYSTEM

Smart Eye Pro (Smart Eye AB, Gothenburg, Sweden) was used to track the driver's eye movement parameters in this research. With the help of 2 infrared lamps, 3 cameras were positioned to observe the blink frequency, saccade velocity and other parameters, as shown in Fig. 2.

TABLE 4. Generalized gray Euclidean distances of evaluation indices.

Cluster centers	m_1 =M-SC	m_2 =PSV	m_3 =SD-LV	m_4 =M-BD	m_5 =SD-BD	m_6 =SD-PSV	m_7 =SD-LAV
M-SC	0.001	0.001	0.001	0.001	0.001	0.001	0.001
SD-SV	0.639	0.603	0.636	0.447	0.690	0.553	0.806
M-BF	0.521	0.664	0.701	0.690	0.458	0.585	0.540
SD-BF	0.620	0.614	0.574	0.638	0.482	0.637	0.657
PSV	0.806	0.001	0.001	0.001	0.001	0.001	0.001
SD-PSV	0.601	0.547	0.754	0.684	0.638	0.001	0.001
M-BD	0.533	0.721	0.710	0.001	0.001	0.001	0.001
SD-BD	0.642	0.652	0.625	0.679	0.001	0.001	0.001
M-TOV	0.636	0.550	0.550	0.602	0.626	0.512	0.559
SD-TOV	0.501	0.657	0.609	0.504	0.603	0.530	0.593
SD-VA	0.608	0.545	0.632	0.596	0.658	0.646	0.616
M-SWA	0.499	0.589	0.636	0.545	0.665	0.681	0.597
SD- SWA	0.526	0.626	0.564	0.663	0.638	0.599	0.639
M-LV	0.554	0.606	0.623	0.645	0.682	0.579	0.595
SD-LV	0.610	0.717	0.001	0.001	0.001	0.001	0.001
M-LAV	0.548	0.541	0.554	0.528	0.520	0.687	0.702
SD-LAV	0.711	0.517	0.487	0.591	0.681	0.712	0.001
Categories of evaluation indices	M-SC/M-SWA/ SD- TOV/ SD- SWA/ M-LV	PSV/ SD-VA	SD-LV	M-BD/ SD-SV	SD-BD/M-BF/ SD-BF/M-LAV	SD-PSV/ M-TOV	SD-LAV

C. EXPERIMENTAL METHODS

Using mobile phones and more sophisticated operations like using iPod, can significantly reduce drivers' perception of dangerous events [42]. Driver's eye movement behavior was collected to analyze the effect of eye movement on driver's behavior safety during the observation of rearview mirror, answering telephone and navigating tasks [43]. Platten *et al.* [44] analyzed the interactions between primary driving behavior and secondary task behavior. Then they proved drivers who compensate their current demands by behavior adaptations in different factors, depending on the characteristics of a secondary task. Furthermore, display screen or driving both act as an external stimulus, that can affect eye movements [45].

On the basis of existing researches, 6 secondary tasks including Bluetooth call, cell phone call, sending text messages, operating the car-mounted music player, chatting and singing, are chosen to study the driving behaviors. Each driver is required to control the speed between 80 and 90 km/h and drive while performing a secondary task. The corresponding experimental methods are described as follows:

1) Bluetooth Calls. The driver calls the lab assistant by using a Bluetooth headset and the lab assistant asks the driver 20 simple questions.

2) Cell Phone Calls. The driver calls the lab assistant by using a hand-held mobile phone and the lab assistant asks the driver 20 simple questions.

3) Sending Text Messages. Drivers and lab assistants are required to send text messages to each other and answer questions from the lab assistants several times for more than 10 minutes.

4) Operating Car-Mounted Players. The driver follows lab assistant directions for operating the car-mounted music player, searches for songs and plays them in the music player, and switches among 5 designated songs one after another, with each song being played for two minutes.

5) Chatting. The driver verbally answers 20 simple questions from the lab assistant.

6) Singing. The driver sings 3 songs with which he/she is familiar and each song lasts for two minutes.

V. RESULTS AND ANALYSIS

A. CHARACTERISTIC EVALUATION INDEX SYSTEM

After the experiment, 17 types of secondary task variable parameters can be measured, which constitute the complete sample of the evaluation indices, which is denoted as $X = X_1, X_2, \cdots, X_{17}$. Then, Deng's gray incidence matrix R of the evaluation indices is obtained via (2 to 5), $R_{17\times 17}$, as shown at the bottom of the next page.

The generalized gray Euclidean distances between each index and the cluster centers were obtained by (6) and are listed in Table 4. The gray incidence clustering method is used to classify the evaluation indices into seven categories [46]. According to the generalized gray Euclidean distance of each index and cluster center, all the indices are clustered into categories. In each category of evaluation indices, the index with the largest R_i is selected as the characteristic evaluation index; the characteristic evaluation indices are listed in Table 5.

B. SELECTION OF CHARACTERISTIC EVALUATION INDEX BY PCA

The overall sample is composed of 17 kinds of candidate evaluation indices which are measured by the experimental equipment. The correlation coefficient matrix is obtained by the Z-score normalization method via (8 to 11). The variance

TABLE 5. Extraction of characteristic evaluation indices.

Evaluation indices	1st cluster category					2nd cluster category		3rd cluster category	
	M-SC	M-SWA	SD- TOV	SD- SWA	M-LV	PSV	SD-VA	SD-LV	
R_i	11.96	12.37	11.85	11.82	12.28	12.36	11.86	12.38	
Characteristic evaluation indices		M-SWA				PSV		SD-LV	
Evaluation indices	4th cluster category		5th cluster category				6th cluster category		7th cluster category
	M-BD	SD-SV	SD-BD	M-BF	SD-BF	M-LAV	SD-PSV	M-TOV	SD-LAV
R_i	12.18	11.92	12.34	11.92	12.33	11.85	12.35	11.59	12.41
Characteristic evaluation indices	M-BD		SD-BD				SD-PSV		SD-LAV

TABLE 6. Data on the average values in six secondary task modes.

		Characteristic evaluation indices						
		PSV	SD-PSV	M-BD	SD-BD	M-SWA	SD-LV	SD-LAV
Secondary task modes	Bluetooth Calls	163.67	7.03	360.04	96.48	0.40	1.82	7.94
	Cell Phone Calls	168.68	9.98	347.27	96.13	0.33	2.13	6.04
	Sending Text Messages	171.74	7.30	338.05	65.37	0.35	2.23	4.89
	Operating Car-Mounted Players	174.52	6.98	344.68	62.50	0.34	2.19	4.85
	Chatting	163.35	6.41	358.87	85.68	0.30	2.22	5.51
	Singing	167.05	9.23	347.13	97.81	0.31	2.03	5.57

contribution rates and cumulative variance contribution rates of correlation coefficient matrix are calculated according to (13 to 14). As shown in Table 7.

From Table 7, the cumulative variance contribution rates of the first 8 evaluation indices is 86.297%, indicating that these 8 indices have included 86.297% of the information in the original sample. The threshold of this study is set to 85%, so the rest of candidate evaluation indices could be discarded, then get the principal components after dimension reduction are obtained. The characteristic evaluation indices that selected by PCA are: SD-LV, M-LAV, M-BF, M-SWA, PSV, SD-PSV, M-BD, SD-BD. Compared with the characteristic indices system established by gray incidence clustering method, 7 indices selected by PCA were repeated with them, which proves that the evaluation indices system established by gray system is feasible.

C. WEIGHT CALCULATION OF DRIVING BEHAVIOR MODES BASED ON THE ENTROPY WEIGHT METHOD

The characteristic evaluation index system includes PSV, SD-PSV, M-DB, SD-BD, M-SWA, SD-LV, and SD-LAV. Within the six secondary task modes, the original data of the seven characteristic evaluation indices of the 40 drivers are averaged, as shown in Table 6.

The data in Table 5 were used to construct and normalize the entropy weight decision-making matrix. Then, the objective weights of the driving behavior modes were obtained according to the entropy weight method via (8 to 11), as shown in Table 8.

$$R_{17\times17} = \begin{bmatrix}
1 & 0.73 & 0.61 & 0.71 & 0.89 & 0.69 & 0.62 & 0.73 & 0.73 & 0.59 & 0.70 & 0.58 & 0.62 & 0.64 & 0.70 & 0.64 & 0.80 \\
 & 1 & 0.53 & 0.67 & 0.69 & 0.64 & 0.53 & 0.78 & 0.59 & 0.59 & 0.60 & 0.78 & 0.71 & 0.73 & 0.73 & 0.72 & 0.90 \\
 & & 1 & 0.67 & 0.75 & 0.67 & 0.78 & 0.55 & 0.54 & 0.81 & 0.57 & 0.79 & 0.74 & 0.85 & 0.79 & 0.65 & 0.63 \\
 & & & 1 & 0.70 & 0.72 & 0.72 & 0.57 & 0.68 & 0.72 & 0.69 & 0.73 & 0.78 & 0.78 & 0.66 & 0.78 & 0.74 \\
 & & & & 1 & 0.63 & 0.81 & 0.74 & 0.64 & 0.75 & 0.63 & 0.67 & 0.72 & 0.69 & 0.80 & 0.63 & 0.60 \\
 & & & & & 1 & 0.77 & 0.72 & 0.60 & 0.62 & 0.74 & 0.77 & 0.69 & 0.67 & 0.84 & 0.78 & 0.80 \\
 & & & & & & 1 & 0.76 & 0.69 & 0.59 & 0.69 & 0.63 & 0.75 & 0.73 & 0.80 & 0.62 & 0.68 \\
 & & & & & & & 1 & 0.72 & 0.69 & 0.75 & 0.75 & 0.73 & 0.77 & 0.71 & 0.61 & 0.77 \\
 & & & & & & & & 1 & 0.65 & 0.63 & 0.80 & 0.65 & 0.75 & 0.64 & 0.62 & 0.65 \\
 & & & & & & & & & 1 & 0.79 & 0.70 & 0.63 & 0.67 & 0.70 & 0.66 & 0.68 \\
 & & & & & & & & & & 1 & 0.60 & 0.71 & 0.67 & 0.72 & 0.67 & 0.71 \\
 & & & & & & & & & & & 1 & 0.62 & 0.72 & 0.72 & 0.82 & 0.68 \\
 & & & & & & & & & & & & 1 & 0.55 & 0.65 & 0.55 & 0.73 \\
 & & & & & & & & & & & & & 1 & 0.71 & 0.67 & 0.68 \\
 & & & & & & & & & & & & & & 1 & 0.64 & 0.57 \\
 & & & & & & & & & & & & & & & 1 & 0.79 \\
 & & & & & & & & & & & & & & & & 1
\end{bmatrix}$$

TABLE 7. Variance contribution rates and cumulative variance contribution rates.

Evaluation Index	Characteristic Root	Variance Contribution Rate	Cumulative Variance Contribute Rate
SD-LV	3.483	20.488	20.488
M-LAV	2.591	15.241	35.729
M-BF	2.122	12.483	48.212
M-SWA	1.663	9.783	57.995
PSV	1.625	9.557	67.553
SD-PSV	1.243	7.309	74.862
M-BD	1.100	6.470	81.332
SD-BD	0.844	4.966	86.297
M-TOV	0.673	3.960	90.257
SD-TOV	0.552	3.248	93.505
SD-VA	0.400	2.354	95.859
SD-BF	0.375	2.206	98.066
SD- SWA	0.188	1.105	99.171
M-LV	0.080	0.471	99.642
M-SC	0.041	0.242	99.884
SD-SV	0.014	0.080	99.964
SD-LAV	0.006	0.036	100.000

TABLE 8. Weights of six driving behavior modes and their rankings.

Driving behavior modes	Bluetooth Calls	Cell Phone Calls	Sending Text Messages	Operating Car-Mounted Players	Chatting	Singing
Weights	0.164	0.160	0.172	0.174	0.169	0.161
Rankings	4	6	2	1	3	5

D. RESULTS

In the experiment, 17 types of evaluation indices were gathered and classified into 7 categories using the Gray incidence clustering method and the characteristic evaluation indices were selected from each category. Then, the characteristic evaluation index system was established. Based on this, a decision-making matrix, which is composed of driving behavior modes and characteristic evaluation indices, was calculated. The entropy weight method was used to obtain the objective weights of 6 secondary task modes. The secondary task modes, in descending order of weight, are as follows: Operating Car-Mounted Players, Sending Text Messages, Chatting, Bluetooth Calls, Singing, and Cell Phone Calls. It is concluded that Operating Car-Mounted Players has the greatest impact on safety and Cell Phone Calls has the least influence on safety among the six secondary-task driving behavior modes.

VI. CONCLUSIONS

In this paper, an eye movement tracking system and a vehicle running state tracking system are used to build the experimental platform for secondary-task driving-behavior-mode safety research. In the secondary-task driving experiment, 40 drivers were recruited to carry out 6 driving behavior modes, and 17 indicative parameters were collected as evaluation indices. The gray incidence clustering method was applied to cluster analysis. Seven characteristic evaluation indices were extracted by using the generalized gray Euclidean distance. Based on these characteristic evaluation indices, the entropy weight method was used to obtain the weight of each driving behavior mode, whose value reflects its relevant importance. The weight value of Operating Car-Mounted Players is 0.174, which indicates that it has the greatest influence on driving safety. In contrast, the Cell Phone Calls weight value is 0.160, which indicates that it has the least impact on driving safety.

The evaluation indices system established in this paper can reflect the change rule of driver's behavior typically, limited by experimental conditions, the experimental participants are biased towards young adults and middle-aged adults in university. Although it cannot cover all types of people, from the point of view of whole sample, the people's educational background and quality are at the upper level of society, so the drivers' comprehension of the experimental target is thorough and their experimental operation is better. Furthermore, the impact of secondary tasks have not been compared to the absence of secondary tasks on driving behavior, this would be improved in the next stage. However, from the perspective of transportation safety, the evaluation index system we established that contains weight of each index, is important for later secondary-task driving safety research, and its methodology is also valuable for drivers' behavior research. As for the promotion of traffic safety development, the importance of drivers' behavior can provide valuable reference for traffic supervision department, driving test center, intelligent network vehicles and so on.

COMPETING INTERESTS

The authors declare no competing interests.

AUTHOR CONTRIBUTIONS

Baicang Guo wrote the main manuscript text. Lisheng Jin established the experimental platform and provided financial support. Fangrong Wang embellished the manuscript. Yuying Jiang is the corresponding author. Xianyi Xie and Ming Gao assisted in the completion of the experimental work. All authors have reviewed the manuscript.

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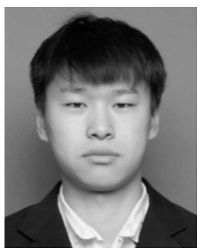

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