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Assessment of drivers' comprehensive driving capability under man-computer cooperative driving conditions

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ABSTRACT The effective assessment of drivers' driving capability under the condition of an advanced driver assistance system is of great significance to the precise switching of driving rights between human and machine and the promotion of the development of man-computer collaboration. In this study, real-time collected warning data from bus driver state monitoring system (DSMS) and advanced driver assistance system (ADAS) were utilized to determine the drivers' comprehensive driving capability indicators. The information utility and interaction of the indicators were considered, and an integrated weight method based on standard deviations was proposed. This method was used to combine the entropy weight method and improved analytic network process (ANP), to evaluate the drivers' comprehensive driving capability under man-computer cooperative driving conditions in real time. The results show that the entropy weight method and improved ANP algorithm have good consistency and are significantly correlated and that the integrated weight method is effective and dependable. The top four indicators in the integrated weighting results were eye closure (0.241), yawn (0.210), rapid deceleration (0.186), and lane departure (0.159). Drivers' comprehensive driving capability scores were concentrated in the score range of 1 to 6, with the lowest scores in zones A and B for stages 2, 11 and 21. Therefore, it is necessary to further explore the relationship between driver behavior, vehicle status and road traffic environment within the score range of 1 to 6 so that the man-computer interaction can be optimized and the driver's comprehensive driving capability can be improved.

INDEX TERMS advanced driver assistance systems, driving capability, entropy weight method, improved ANP, man-computer cooperative driving.

I. INTRODUCTION

With the rapid development of computer technology, Internet technology, communication technology and artificial intelligence, intelligent vehicles based on electrification, intelligence and network connectivity have become a major trend in the automotive industry. According to the development process of intelligent and automated vehicles, the U.S. Department of Transportation, SAE, etc. [1] have classified the development of the intelligent vehicle into six levels: no automation, driver assistance, partial automation, conditional automation, high automation, and full automation. Although different levels

and functions of intelligent vehicle technology are developing rapidly, a fully working automatic driving vehicle has been difficult to achieve in the short term [2]. We have only entered the initial stage of man-computer cooperative driving in which drivers and automatic driving systems collaborate with each other [3], and intelligent vehicles from L1 to L4 levels have to face man-computer cooperative control problems. Furthermore, in the process of man-computer cooperative driving, the most important component has been the distribution of driving rights and cooperation [4]. Ghasemi et al. [5] also agreed that the

critical point of man-computer cooperation is to determine the driving rights between the driver and the control system.

Especially in the L1 and L2 stages, when drivers' states are abnormal, their driving ability cannot meet the current driving requirements. Deficiencies in the driver's operation would be compensated by the control system, or the intelligent driving terminal would take over the driving right (such as automatic emergency braking system) to realize the safe control of the man-computer cooperatively driven vehicle. However, in actual man-computer switching studies, it was found that factors such as an inaccurate assessment of the driver's own driving capability [6], [7], driving load [8], and inadequate driver self-perception [9] often caused conflicts in the vehicle driving right switching process, which would most likely cause serious consequences such as a loss of control of the vehicle. To effectively control the timing and strength of the assisted compensation, assist the driver's self-awareness, and ensure the reasonableness of the transfer of driving rights, it is necessary to research the current method of evaluating the driver's capability under a driving load. The purpose of this study is to provide a scientific basis for the intelligent driving assistance system to control the timing of the assisted compensation, determine the strength of the assisted compensation, and assign driving rights. It also assists the driver's self-awareness process and ensures that the transfer of driving rights is reasonable.

A person's driving ability is an ambiguous concept, the essence of which is the construction of driving behavior representation indicators and analysis methods [10]. It is determined by driving style, driving skill, and physical and cognitive characteristics [11]. In this study, the comprehensive driving capability is represented as an evaluation index that aims to assess whether the driver is effectively able to cope with current traffic conditions, considering the person's driving ability and current driving load. However, the randomness, variety, ambiguity, and individuality of the driver's characteristics as well as the complexity of the traffic environment determine the random, dynamic nature of driving capability. Therefore, driving capability has been difficult to evaluate with a single indicator. Wang and Xu [12] administered the Manchester Driver Behavior Questionnaire (DBQ) to 57 drivers and used logistic regression to explore the relationship between driving behavior and driver risk level, and the driver's comprehensive driving capability in terms of driving risk level was reflected. Isabelle and Simon [13] used different traffic scenarios on a driving simulator to assess drivers' driving capability and self-regulatory behavior. Zhou Xiaoji [14] used the driving simulator of UE4, a professional game engine, to extract various driving characteristics and capability indicators from the data collected in real time. The ANP-BP neural network capability evaluation model was established to estimate the driver's baseline driving capability. Then, a real-time driving capability evaluation model was established based on the dynamic time window and driving risk, to research the man-computer shared

driving-right handover mechanism based on the driving capability margin. Subjective driving behavior questionnaires provide limited objective evidence for the risk assessment of driving behavior. The external validity of the driving simulator's environment has been questioned. Because the real-world fidelity was reduced and the driving motivation was potentially altered (i.e., the driver was aware that he or she was safe in the simulated environment), the validity of the study's findings has been questioned.

To avoid overly subjective driving behavior questionnaires and the distortions caused by driving simulators, Aihong Lv et al. [15] proposed a method for assessing driver stress reactivity based on the braking deceleration safety distance model, in which data on driving operation behavior and vehicle motion were used. The objective data on driver and vehicle movements were used effectively; however, the research on driver competence was limited to driver stress, and comprehensive studies were lacking. Wenli Liu et al. [10] proposed a comprehensive driving capability evaluation method based on a fuzzy network hierarchical analysis algorithm (F-ANP) for group decision making and multi-indicator fusion. However, it was built by using a driving simulator, and the data for many of the indicators were costly to collect in the actual driving environment, which did not have a good generalizability. Additionally, the above research studies only examined the driver's ability to control the safety of the vehicle in terms of driving behavior or vehicle condition indicators before the system warning (or accident) occurred. The best way to explore a person's driving capability under man-computer cooperative control conditions would be to statistically analyze the actual warning data (or accident data) of those vehicles that have been equipped with common forms of automated driver assistance systems [16].

Therefore, in this paper, a driver capability evaluation method for man-computer cooperative driving is proposed, which is based on the real-time collection of warning data from the bus Driver State Monitoring system and the Advanced Driver Assistance System. The utility and interaction of the indicator information were taken into consideration, and an integrated weight method based on the standard deviation was proposed. In this way, the comprehensive driving capability of bus drivers under ADAS conditions can be effectively evaluated with a view to providing scientific evidence for research on the safety prevention and control of man-computer cooperative driving and the precise timing of man-computer driving-right switching.

The paper's framework is as follows. In the next section, Materials and Methods, we introduce the entropy weight method that considers the information utility of the indicators. An improved ANP algorithm based on the relative weight association rule support method is proposed, considering the interactions between the indicators. A comprehensive weighting method based on the deviations in the results is proposed, considering the information utility of the indicators and interactions. Finally, we

introduce the data collection equipment overview and evaluation indicator system. In the third section, Results, we analyze the weighting results of the entropy weight method and the improved ANP algorithm. The necessity and advancement of the integrated weight method are validated. The comprehensive driving capability of six drivers is calculated, and the results of the evaluation for the fifth driver are analyzed with the baseline driving capability and driving load. In the final section, Discussion, we discuss the validity of the method and results of this study as well as the practical implications of the results of each weighting and the comprehensive driving capability evaluation. In addition, relevant recommendations for research on the optimization of interactions in man-computer cooperative driving are proposed.

II. MATERIALS AND METHODS

Due to the complexity of the driving process, the importance and priority of the actual operational indicators were judged mainly on the basis of personal experience. For that reason, the evaluation results usually varied from person to person, which is not conducive to an objective and effective assessment of the driver's capability. Therefore, the search for an objective and comprehensive evaluation method is particularly important for the correct assessment of driving capability. Currently, there are

related integrated methods such as the analytic hierarchy process (AHP), entropy weight method, dispersion maximization method, local variation weight method, analytic network process (ANP) and other evaluation indicator weight determination methods.

Of these methods, the entropy weight method determines the weight by the entropy of the indicator information, which considers the information utility of each indicator. The ANP algorithm has been able to better obtain the interaction between the indicators to determine the indicator weights. However, because the traditional ANP algorithm is too subjective in considering the degree of interaction between indicators, this study proposed an improved ANP algorithm based on the relative weight association rule support method as a more objective way of accounting for the interactions. To consider both the information utility of the indicators and their interaction relationship, a comprehensive weighting method based on the standard deviation of the results was proposed. This method combines the entropy weight method and the improved ANP algorithm to effectively evaluate the driver's comprehensive driving capability for man-computer cooperative driving.

The main variables involved in the methods are shown in Table 1.

TABLE 1.
LIST OF VARIABLES

Variables	Description of variables
E_j	The information entropy for evaluation indicator j
P_{ij}	The probability of the occurrence of the j indicator in the system i state
y_{ij}	The frequency of occurrence of the item j warning type in state i
ΔW_{BC}^A	The value of the degree to which indicator B elements are more important than indicator C elements under the guidelines for indicator A elements
ΔW_{CB}^A	The value of the degree to which indicator C elements are more important than indicator B elements under the guidelines for indicator A elements
W_{ij}^k	The value of the degree to which the i indicator element is more important than the j indicator element relative to the relative importance among all elements under the k criterion.
σ_1, σ_2	The standard deviations of the driving capability results evaluated by the improved ANP algorithm and entropy weighting method
x_{ij}	The base data, i.e., j indicator data in state i

A. ENTROPY WEIGHT METHOD

Entropy has its origins as a concept in thermodynamics and is a measure of the degree of uncertainty about the state of a system. Information entropy is often used in the entropy method to measure the degree of order of the system state [17]. The entropy weight method uses the size of the effective amount of information contained in the data to measure the impact of each indicator on the comprehensive evaluation [18]. The information entropy of each evaluation indicator has been determined by the entropy weight method. The smaller the information entropy, the greater the utility value of the

information provided by the evaluation indicator and the greater the weight assigned to the indicator. Li Shiwu et al. [19] collected data on drivers' eye movement data, reaction time, and execution time in the continuous driving state to quantify drivers' driving fatigue. The entropy weight method was used to determine the three indicator weights of attentional characteristics, reactivity, and execution capacity. The validity of the entropy weight method for determining indicator weights was verified based on the time points of driver fatigue recorded in the experiment.

The greatest advantage of the entropy weighting method is to avoid the subjective judgment of the researcher and to take full advantage of the data to

objectively calculate the weights for each indicator. The principles underlying the entropy weighting method for determining indicator weights are as follows. For a system with n different states and m evaluation indicators, the information entropy E_j for determining the evaluation indicator j in the system is:

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n (p_{ij} \ln p_{ij}) \quad (1)$$

where p_{ij} is the probability of the occurrence of indicator j in system state i .

$$p_{ij} = \frac{y_{ij}}{\sum_{j=1}^m y_{ij}} \quad (2)$$

y_{ij} indicates the frequency of the occurrence of the item j warning type in state i . In particular, when $p_{ij}=0$ (i.e., $y_{ij}=0$), then $p_{ij} \ln p_{ij}=0$. The entropy weight of the j evaluation indicator in this system is:

$$W_j = -\frac{E_j}{m - \sum_{j=1}^m E_j} \quad (3)$$

B. IMPROVED ANP ALGORITHM

The Analytic Network Process (ANP) is a multicriteria decision method based on the AHP and was proposed to analyze nonindependent graded hierarchies to address systematic decision problems with feedback or interaction between indicator elements [20], [21]. The ANP is widely used to solve real-world problems due to its consideration of the complex and interrelated relationships among decision elements and its ability to apply both qualitative and quantitative properties [22].

1) THE RELATIVE WEIGHT ASSOCIATION RULE SUPPORT METHOD

The first task in constructing the ANP evaluation model is to determine the relative importance of two indicator elements under a certain criterion to obtain the judgment matrix to calculate the supermatrix. The traditional method of determining the discriminant matrix has been mainly the Delphi method (expert method) and the two-two comparative method. It was inevitable that comparative judgments would be made by human beings. Thus, there was a greater human influence and a greater error in the final weighting results. Chen Jianqiu et al. [23] proposed the relative weight expert mean confidence method to reduce the overly subjective nature of the ANP evaluation model to evaluate the control ability of wireless occlusion centers. However, it was still impossible to avoid the subjective influence of humans. To avoid the errors caused by such subjectivity, the relative weight association rule support method was proposed to determine the relative weights between two elements, and the steps are as follows.

Step 1: Mine for interindicator support through systematic clustering and the Apriori association rule

method, such as the probability that indicator A and indicator B occur simultaneously.

Step 2: Calculate the relative importance value between two elements of the indicator under certain criteria, such as:

$$\text{if } B \geq C \text{ then } \Delta W_{BC}^A = \frac{\text{Support}(A \Rightarrow B) - \text{Support}(A \Rightarrow C)}{\text{Support}(B \Rightarrow C)} \quad (4)$$

$$\text{if } B < C \text{ then } \Delta W_{CB}^A = \frac{\text{Support}(A \Rightarrow C) - \text{Support}(A \Rightarrow B)}{\text{Support}(A \Rightarrow B)} \quad (5)$$

where ΔW_{BC}^A indicates the value of the degree to which indicator B elements are more important than indicator C elements under the guidelines for indicator A elements; ΔW_{CB}^A is similarly calculated.

Step 3: Calculate the relative importance values between all indicator elements for a certain criterion and obtain a judgment matrix for that criterion.

$$W_{ij}^k = \frac{\Delta W_{ij}^k - \min(\Delta W_{ij}^k)}{\max(\Delta W_{ij}^k) - \min(\Delta W_{ij}^k)} \quad (6)$$

where W_{ij}^k denotes the value of the degree to which the i indicator element is more important than the j indicator element relative to the relative importance between all elements under the k criterion.

Step 4: Return to Step 2 until the judgment matrix of all the criteria is obtained and proceed to Step 5.

Step 5: Professor Satty's Super Decision software has been introduced to visually show the correlation between the indicator elements and quickly obtain the calculation results to realize the ANP evaluation model solution. Therefore, the values of the elements in each judgment matrix should be blurred on a scale of 1–9 [24] to obtain the standard judgment matrix.

2) THE OPERATIONAL PROCESS OF THE IMPROVED ANP MODEL

The improved ANP model process based on the relative weight association rule support method is shown in Figure 1. The model control layer and network layers were identified to obtain the complete ANP evaluation model structure. The control layer contained the objectives and decision criteria for the identified decision-making issue (objective layer, criteria layer). The network layer element was composed of elements that were governed by the control layer and that interacted with each other (feedback, interaction). The systematic clustering preprocessing of the base warning data was performed to obtain the base data that were complied with the Apriori association rule mining. The support between the indicator elements was mined using the Apriori algorithm. The relative weight association rule support method proposed above was used to identify the standard judgment matrix and perform a consistency test. After passing the test, the characteristic vectors of the matrices were calculated to constitute the unweighted supermatrices of the driving capability assessment. The cluster weights and unweighted supermatrix were applied to

obtain a weighted supermatrix that can reflect the dependencies between clusters. The weighted supermatrix

was stabilized to obtain the limit-weighted supermatrix and finally the global weights of all indicator elements.

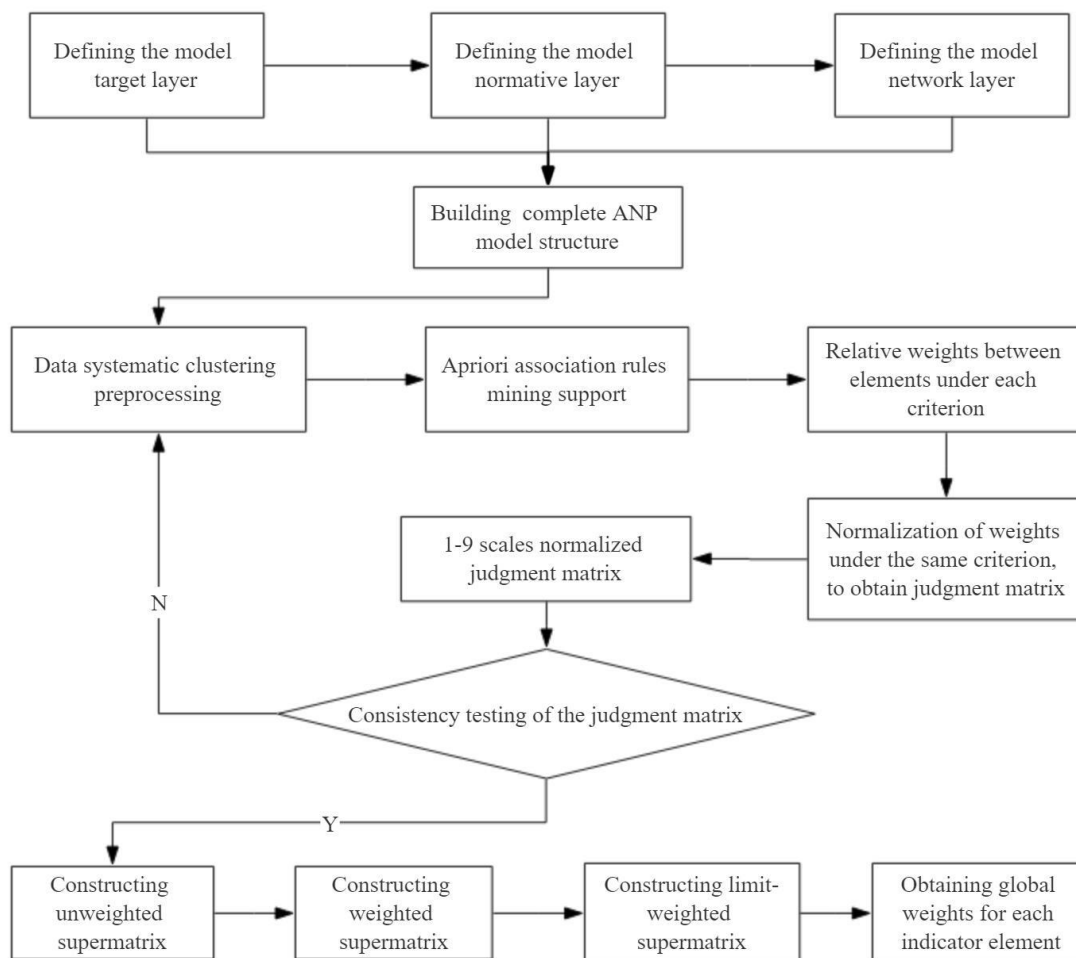


FIGURE 1. Calculation procedure of the improved ANP evaluation model

C. INTEGRATED WEIGHT METHOD

The determination of the weights directly affects the results of the comprehensive evaluation, and changes in the weight values directly affect the ranking of the importance of the evaluation indicators and may even cause changes in the order of merit of the evaluated subjects. Therefore, the scientific determination of indicator weights is of great importance in the comprehensive evaluation. The weights were identified through a combination of the entropy weight method and improved ANP algorithm, which recognized the informational utility of the indicators and the interaction between them. In addition, the arbitrariness of subjective empowerment was avoided. Weights of $W_1(j)$ and $W_2(j)$ were obtained on the basis of the improved ANP algorithm and entropy weight method, respectively. To balance the advantages of the improved ANP algorithm and entropy weight method, the standard deviations of the evaluation results of the two methods were considered. The weights of the two algorithms were fused to reduce the deviation in their weights to fully and effectively assess the

drivers' comprehensive driving capability. Assuming a final weighting value of $W(j)$ for each of the multidimensional indicators, by the integrated weight method, the following are obtained:

$$\sigma_1 = \sqrt{\frac{1}{N} \sum_{i=1}^n \left(\sum_{j=1}^m W_1(j) X_{ij} - \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^m W_1(j) X_{ij} \right)^2} \quad (7)$$

$$\sigma_2 = \sqrt{\frac{1}{N} \sum_{i=1}^n \left(\sum_{j=1}^m W_2(j) X_{ij} - \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^m W_2(j) X_{ij} \right)^2} \quad (8)$$

$$W(j) = \frac{\sigma_1 W_2(j) + \sigma_2 W_1(j)}{\sigma_1 + \sigma_2} \quad j = 1, 2, \dots, m \quad (9)$$

where σ_1 , σ_2 are the standard deviations of the driving capability results evaluated by the improved ANP algorithm and entropy weighting method, respectively; x_{ij} is the base data, i.e., the j indicator data in state i ; $W(j)$ is the integrated weight of the j indicator; and m is the number of indicators. The data for each type of warning were

processed, and the number of warning events of each type over a period of time was counted, which resulted in the basic data for the j evaluation indicator element in state i .

D. EQUIPMENT OVERVIEW AND EVALUATION INDICATOR STRUCTURE

1) EQUIPMENT OVERVIEW AND DATA

The research data in this study were obtained from the Bus Driver State Monitoring System (DSMS) and Advanced Driver Assistance System (ADAS) in Zhenjiang City. The front-end equipment mainly consists of an intelligent driving terminal and DVR vehicle data recorder installed on the bus. The intelligent driving terminal, which

contains a fatigue detection camera from the built-in fatigue driving warning system, an ADAS camera and an active safety warning system loudspeaker. It is used to collect the real-time video warning data from the bus driver. The DVR vehicle data recorder is composed of a video displayer and two DVR vehicle data recorders. It can cooperate with the intelligent driving terminal to realize the real-time data acquisition of the radar warning data from the bus, the vehicle in front and the driving characteristics of the bus driver. The video displayer is used to display the images captured by the camera of the DVR vehicle data recorder. The layout of the equipment is shown in Figure 2.

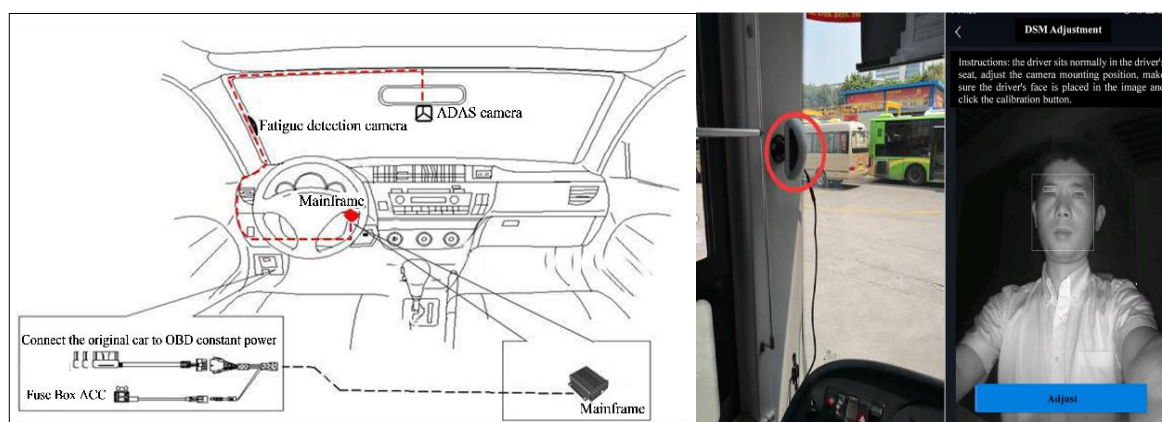


FIGURE 2. Equipment layout

The data consisted of the warning data for bus drivers (eye closure, yawn, looking away) and vehicles (lane departure, rapid acceleration, rapid deceleration, forward collision).

In this study, 91,964 points of warning data from public transport vehicles in Zhenjiang were collected from February 2019 to March 2019 (partial dates), and a total of

29,813 valid data points were selected after data cleaning. The data characteristics included: warning time, warning type, warning location (latitude and longitude), vehicle line, vehicle license plate number, and driver's number. Each type of warning trigger criteria and sample size is shown in Table 2.

TABLE 2.
DESCRIPTION OF THE TRIGGER FOR EACH TYPE OF WARNING

Warning type	Condition for triggering the warning system	Sample size
Eye closure	The warning system will be triggered when the driver's eyes keep closed for a long time while driving.	5944
Yawn	The warning system will be triggered once the driver yawns while driving.	5687
Looking away	The warning system will be triggered when the driver keeps looking to the left or right for over 5 s.	1221
Lane departure	The warning system will be triggered once the vehicle's speed exceeds 55 km/h and deviates from the lane to cross the lane line, except when the vehicle's turn signal is on, the lane change occurs in acceleration/deceleration state, the vehicle switches lanes rapidly, there is no line or the lane lines are not clear.	4484
Rapid acceleration	The warning system will be triggered once the longitudinal acceleration change value exceeds the corresponding threshold value prescribed by the SGS safety standard.	1961
Rapid deceleration		5983
Forward collision	The warning system will be triggered once the vehicle's speed exceeds 55 km/h or when the vehicle is running at a constant speed of over 30 km/h and meanwhile its relative speed is faster than the vehicle in the front of it and the relative time distance (the distance between the vehicle's head and the tail of its front vehicle/(vehicle speed – speed of the front vehicle)) is within 3 s.	4534

2) THE DRIVING CAPABILITY ASSESSMENT INDICATORS STRUCTURE

To avoid the temporal variability and uncertainty of the psycho-physiological state in traditional driver characteristic research, the driver was treated as a "black box" system, which contains various factors reflecting driving capability from the driver's perspective, such as the driver's physical and mental state, driving style, driving skill level, and adaptability to the traffic environment. The

vehicle was treated as another "black box" system, which contains various factors reflecting driving capability from the vehicle's perspective, such as the vehicle performance, instantaneous failure, and the driver's control of the vehicle. The driver's capability in the current road environment was objectively analyzed on the basis of the warning results (warning data) caused by the integrated response of the "black box" system.

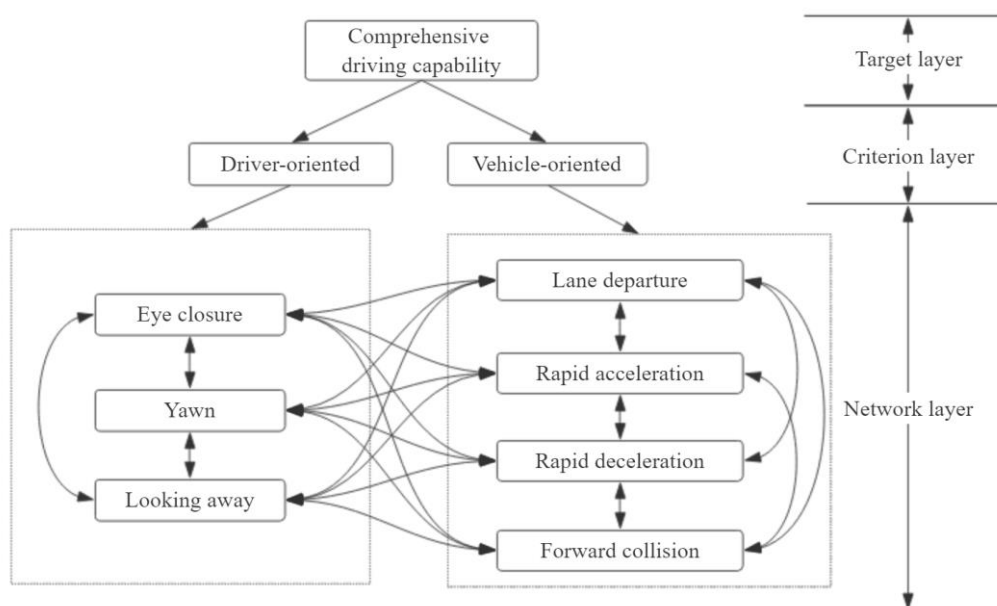


FIGURE 3. ANP evaluation model of comprehensive driving capability

The essence of driving capability is the construction and application of driving behavior characterization indicators and analytical methods. The indicators not only need to meet the needs of real time but also need to have adaptive mechanisms so that they can be applied to different road conditions and drivers with different characteristics [15]. In this study, the real-time warning data for drivers and vehicles caused by the driver's driving behavior in the current complex traffic environment were utilized. This information not only met the needs of the real-time indicators but was also strongly adaptable (different drivers' driving behavior is different, and the triggering of system warnings is also different); therefore, it also met the needs of the indicator adaptive mechanism.

Thus, a structure of indicators for evaluating driving capability was constructed in this study from two viewpoints: "driver-oriented" and "vehicle-oriented" alerts. Driving capability was used as the evaluation target (target layer), warning-oriented object (driver, vehicle) as the evaluation criterion (criterion layer), and eye closure, yawn, looking away, lane departure, rapid acceleration, rapid deceleration, and forward collision as the network layer evaluation indicator elements to establish a driver capability evaluation model based on the improved ANP algorithm, as shown in Figure 3.

TABLE 3.
RELATIONSHIPS BETWEEN ELEMENTS

Element s	Description	Relationship
A	Comprehensive driving capability	B1、B2
B1	Driver-oriented	C1、C2、C3
B2	Vehicle-oriented	C4、C5、C6、C7
C1	Eye closure	C2、C3、C4、C5、C6、C7
C2	Yawn	C1、C3、C4、C5、C6、C7
C3	Looking away	C1、C2、C4、C5、C6、C7
C4	Lane departure	C1、C2、C3、C5、C6、C7
C5	Rapid acceleration	C1、C2、C3、C4、C6、C7
C6	Rapid deceleration	C1、C2、C3、C4、C5、C7
C7	Forward collision	C1、C2、C3、C4、C5、C6

3) DEPENDENCIES AMONG INDICATOR ELEMENTS

The relationships among the indicator elements were obtained from Figure 3 and are shown in Table 3, in which the third column indicates the dependencies between the elements. The driving capability (element A) is affected by both driver (B1) and vehicle (B2), while driver-oriented

warnings consist of eye closure, yawn and looking away; therefore, elements C1 to C3 are affected by element B1.

Vehicle-oriented warnings consist of lane departure, rapid acceleration, rapid deceleration and forward collision, so element B2 is affected by elements C4 to C7. After the warning data were cleaned and a Pearson correlation analysis conducted, the results showed that the correlation coefficient between the two warning types was greater than 0.9, and the level of significance was less than 0.01. The correlation between the warning types was significant, and the interactions were obvious; therefore, there was a dependence between the two.

III. RESULTS

A. WEIGHTS BASED ON THE ENTROPY WEIGHT METHOD

The warning data from all drivers were considered, and the entropy weighting method was applied to calculate the weights for each indicator, as shown in Figure 4.

The indicators, in descending order of information utility (weights), were eye closure (weight 0.236), rapid deceleration (weight 0.212), yawn (weight 0.189), lane departure (weight 0.181), forward collision (weight 0.128), rapid acceleration (weight 0.054), and looking away (weight 0.000). Since the occurrence of the looking away warning was low and could provide less valid information, the information entropy of the looking away indicator was calculated to be $E_3 = 0.359 < 1$, i.e., the weight was less than 0 (not in line with the actual); therefore, the weight of the indicator (i.e., 0) was excluded.

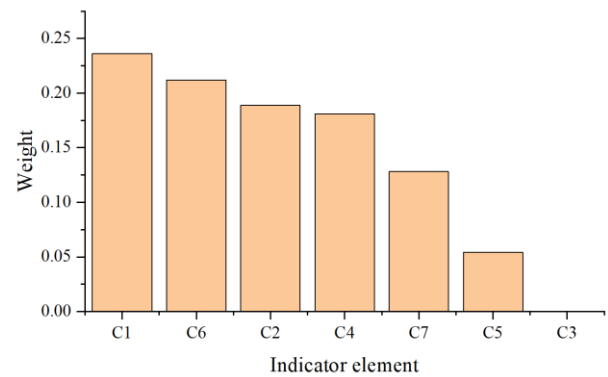


FIGURE 4. Priority weight of indicator elements based on the entropy weight method

B. WEIGHTS BASED ON THE IMPROVED ANP ALGORITHM

Based on the driving capability evaluation indicator structure, an ANP link structure that the Superdecision software could recognize was established. The improved ANP model used the proposed relative weight association rule support method to mine the degree of association between elements from the warning data to determine the weights between two elements to form a standard judgment matrix. The consistency test results showed that the consistency coefficients of the various judgment matrices were less than 0.1, which indicated that the weights were acceptable, and the relative weight association rules support method was valid and reliable. The eigenvectors of each matrix were computed, and the unweighted supermatrix was constructed. After the weighting and stability treatment, the limit-weighted supermatrix was obtained, as shown in Table 4.

TABLE 4.
LIMIT-WEIGHTED SUPERMATRIX

	Vehicle-oriented	Driver-oriented	Comprehensive driving capability	Forward collision	Looking away	Rapid deceleration	Rapid acceleration	Yawn	Lane departure	Eye closure
Vehicle-oriented	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Driver-oriented	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Comprehensive driving capability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Forward collision	0.03529	0.03529	0.03529	0.03529	0.03529	0.03529	0.03529	0.03529	0.03529	0.03529
Looking away	0.03741	0.03741	0.03741	0.03741	0.03741	0.03741	0.03741	0.03741	0.03741	0.03741
Rapid deceleration	0.14820	0.14820	0.14820	0.14820	0.14820	0.14820	0.14820	0.14820	0.14820	0.14820
Rapid acceleration	0.16319	0.16319	0.16319	0.16319	0.16319	0.16319	0.16319	0.16319	0.16319	0.16319
Yawn	0.24153	0.24153	0.24153	0.24153	0.24153	0.24153	0.24153	0.24153	0.24153	0.24153
Lane departure	0.12567	0.12567	0.12567	0.12567	0.12567	0.12567	0.12567	0.12567	0.12567	0.12567
Eye closure	0.24871	0.24871	0.24871	0.24871	0.24871	0.24871	0.24871	0.24871	0.24871	0.24871

The identical values in the rows of the limit-weighted supermatrix indicated that the matrix was stable. The size of the individual values in each column determined the order of importance of their corresponding elements, as shown in Figure 5. The main factors that affect the driving capability of bus drivers were, in order, eye closure (weight

0.24871), yawn (weight 0.24153), rapid acceleration (weight 0.16319), rapid deceleration (weight 0.14828), and lane departure (weight 0.12567). Among these factors, the highest weight occurred with the driver's eye closure warning, while the driver's looking away warning (weight 0.03741) had a smaller weight. Due to the lower number of

warnings, the association with the other warning types was weaker, which was consistent with the entropy weight method. The smaller weight of the vehicle forward collision warning (weight of 0.03529) was caused by the relatively more concentrated occurrence of the actual road environment, thus the relatively smaller association with the other warning types.

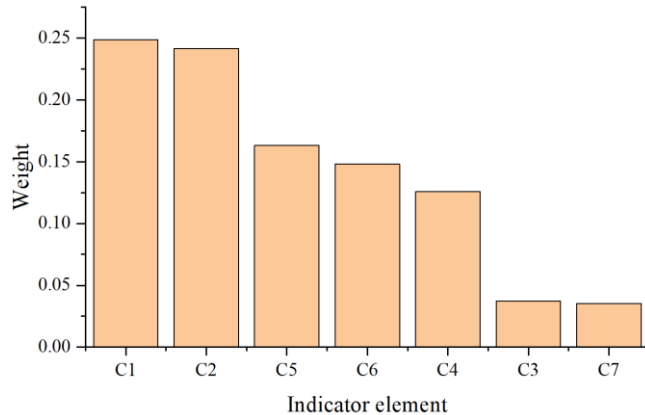


FIGURE 5. Priority weight of indicator elements based on improved ANP

C. ASSESSMENT AND ANALYSIS OF COMPREHENSIVE DRIVING CAPABILITY

1) INTEGRATED WEIGHTS TEST AND DETERMINATION

To further demonstrate the degree of influence of the entropy weight method, improved ANP algorithm and integrated weight method on the bus driver capability evaluation, their radar maps were plotted with the weights from each method, as shown in Figure 6.

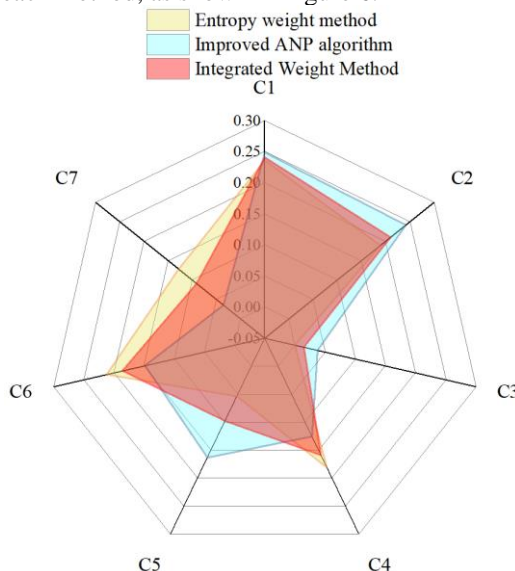


FIGURE 6. Radar map of evaluation indicator weights

The figure shows the distribution of the weights of the evaluation indicators under the three methods, with the values of the weights gradually increasing from the center of the network outward. The integrated weight closed region basically covers the closed regions of the entropy weight method and improved ANP algorithm. This figure shows that the integrated weights reflect the data of both the evaluation indicators and their interactions. Furthermore, the integrated weighting results were in the order of eye closure (0.241), yawn (0.210), rapid deceleration (0.186), lane departure (0.159), rapid acceleration (0.098), forward collision (0.091) and looking away (0.015).

2) DRIVING CAPABILITY ASSESSMENT RESULTS TEST

The weights of the improved ANP, entropy weight and integrated weight methods were adopted to assess the comprehensive driving capability of driver No. 5. The driving capability evaluation indicators were normalized, and the driving capability of each stage state was fuzzed to 1 to 10, as shown in Figure 7.

With the change in driving status, the changes in the driving capability of the improved ANP algorithm and entropy weight method had the same trend. Therefore, the results of the improved ANP algorithm and entropy weight method have a better consistency. To further validate the direct correlation between the results of the improved ANP algorithm and the results of the entropy weight method, a Pearson correlation analysis was performed on the results of both assessments. The results showed that the correlation coefficient was 0.997 and the significance P value was 0.000 at the significance level of 0.05, which passed the significance test. There was a good agreement and significant correlation between the overall trends of the two methods, and the weighting results of the two algorithms could be fused.

As seen from Figure 7, the entropy weight method focused too much on the informational utility of the indicators themselves and did not consider the interaction between the indicators. Therefore, the results of the comprehensive driving capability evaluation were significantly higher. The improved ANP algorithm described the interaction between the indicators more objectively than did the traditional ANP algorithm but ignored the information utility of the indicators themselves, resulting in low evaluation results. Therefore, the integrated weight method proposed in this paper could effectively avoid the inadequacies of the two algorithms and fully consider the information utility of the indicators themselves and the interaction between the indicators, to evaluate the driver's driving capability in a more reasonable and effective way.

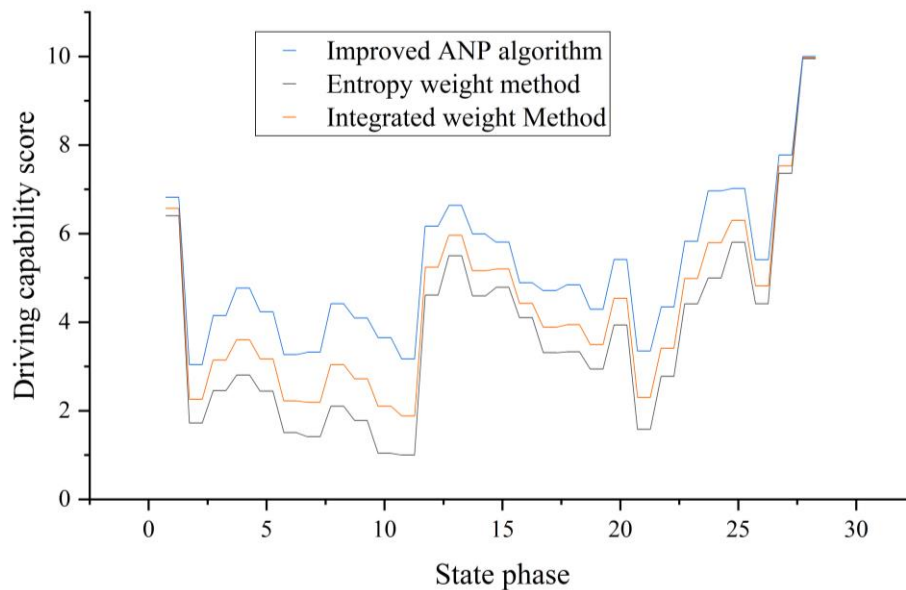


FIGURE 7. Comparison of driving capability evaluation results of driver No. 5

3) ANALYSIS OF THE DRIVING CAPABILITY ASSESSMENT RESULTS

The warning data for six drivers were selected, and the comprehensive driving capability scores for each of the six drivers were calculated using the integrated weight method.

The scores for each driver were fuzzed from 1 to 10, and the fuzzy scores were averaged to obtain the mean, which served as the baseline driving capability. The comprehensive driving capability and the baseline driving capability curve of the six drivers are shown in Figure 8.

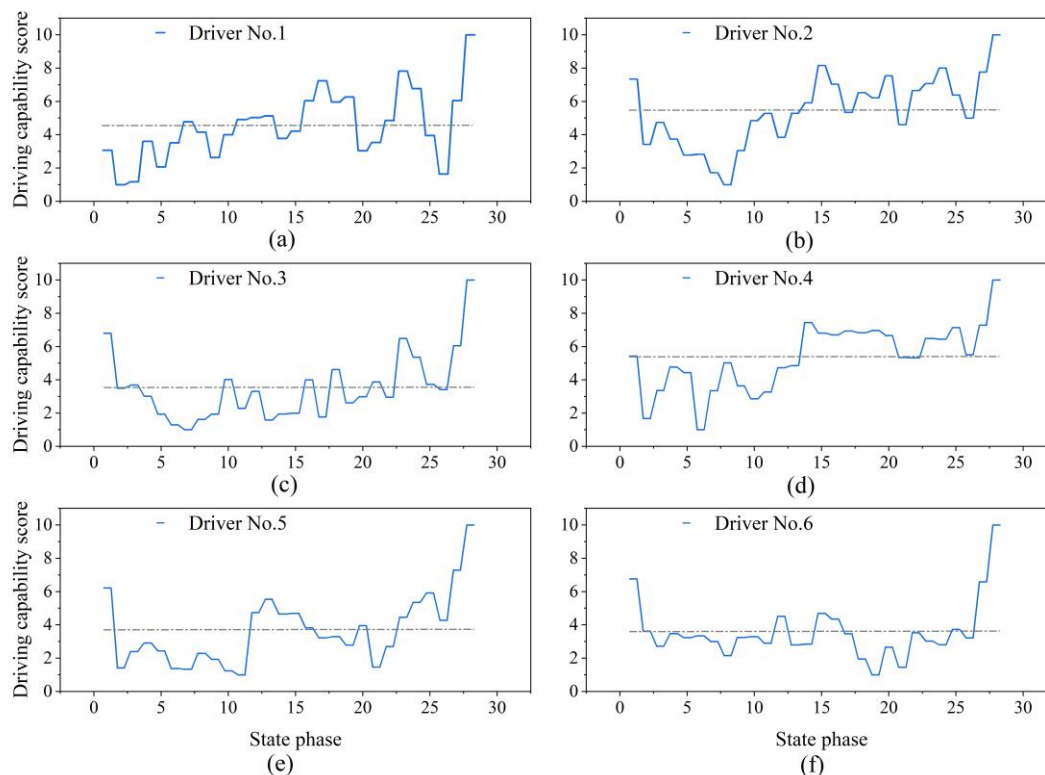


FIGURE 8. Comprehensive driving capability of drivers 1 to 6 and baseline driving capability

The tails of the curves show an upward trend, which is because after the evening rush hour, the driving load decreased significantly. This contributes to the

improvement in the drivers' comprehensive driving capability. However, the baseline driving capability values of the six drivers were significantly varied, and the

characteristics of the changes in comprehensive driving capability were significantly different. This indicated that the results of the comprehensive driving ability evaluation were good.

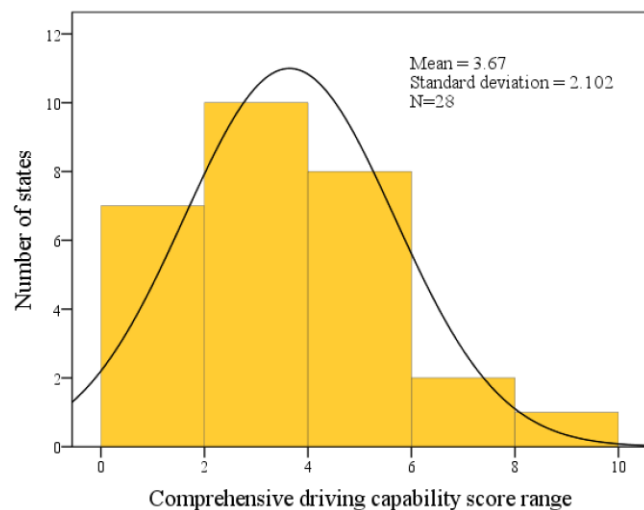


FIGURE 9. Comprehensive driving capability score distribution statistics for driver No. 5

A single-sample Kolmogorov-Smirnov test was performed on the results of each state stage of the comprehensive driving capability evaluation for driver No. 5. The results showed that the asymptotic significance level

was 0.200, which was greater than the significance level of 0.05. Therefore, the driver's driving capability assessment scores followed a normal distribution.

As shown in Figure 9, the distribution of the comprehensive driving capability score of driver No. 5 was mostly in the range of 1 to 6 and tended to be normal. Therefore, the integrated weight method could be used to effectively evaluate the driver's comprehensive driving capability.

The number of warnings triggered in each phase state for driver No. 5 was used to reflect the driver's driving load. The driving load calculation was fuzzed from 1 to 10 and analyzed against the comprehensive driving ability evaluation results of driver No. 5, as shown in Figure 10. The gray dotted line in the graph is the driving load trend line, and the red dotted line is the comprehensive driving capability trend line. The comprehensive driving capability is a comprehensive evaluation indicator that considers the driving load in a complex traffic environment and the driver's ability. Two trend lines were observed. The driving load decreased overall, while the corresponding comprehensive driving capability increased. In addition, during the change in the curve, higher driving load scores tended to correspond to lower comprehensive driving capability scores. In conclusion, this method is accurate and effective in evaluating the comprehensive driving capability of driver No. 5.

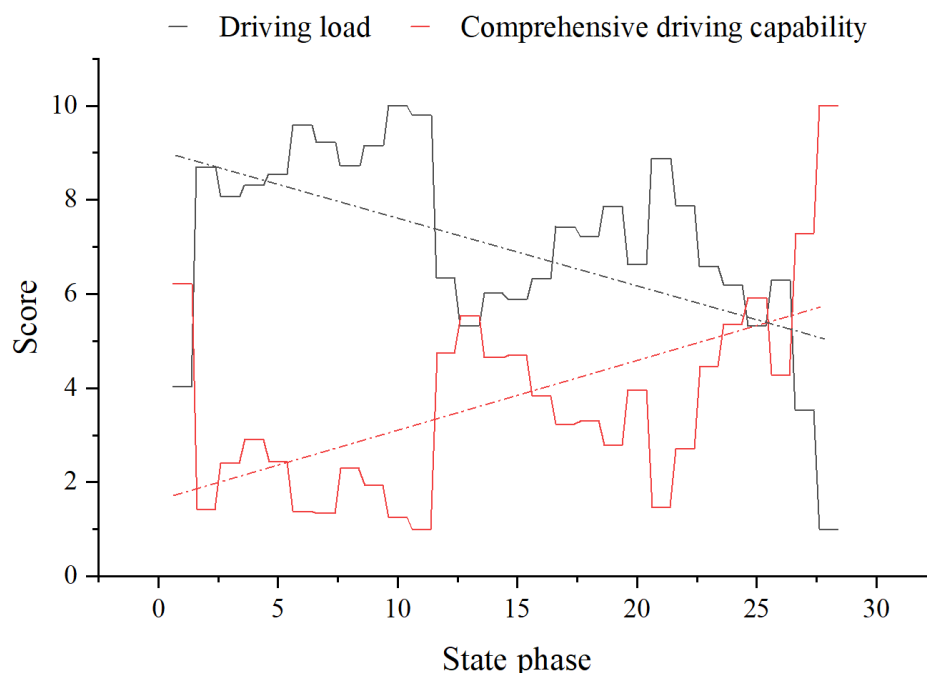


FIGURE 10. Comprehensive driving capability and driving load variation curve for driver No. 5

Based on the characteristics of the driving load, baseline driving capability and comprehensive driving capability curves, the regional distribution of the comprehensive driving capability levels was roughly

divided, as shown in Figure 11. Relative to the driving capability scores within region C, the comprehensive driving capability scores within regions A and B were relatively low, and their corresponding driving loads were

significantly higher. The comprehensive driving capability values in regions A and B were less than the baseline driving capability, particularly in region A. The reason for the increase was mainly due to the complex road traffic environment of the city's morning, middle and evening peaks, which caused the driving load to increase. As the driver's ability did not effectively meet the current driving demand, the system warnings were triggered easily; thus, the comprehensive driving capability score was low.

The comprehensive driving capability score was particularly low in stages 2, 11 and 21, which corresponded to a significantly higher driving load, and all three stages fell within both A and B regions. Stages 1 and 28 were in the peak periods before and after the road traffic pressure is reduced, respectively, when road traffic conditions are relatively simple. The driver ability could better meet the current driving demand and triggers fewer system warnings; thus, its comprehensive driving capability scores were higher.

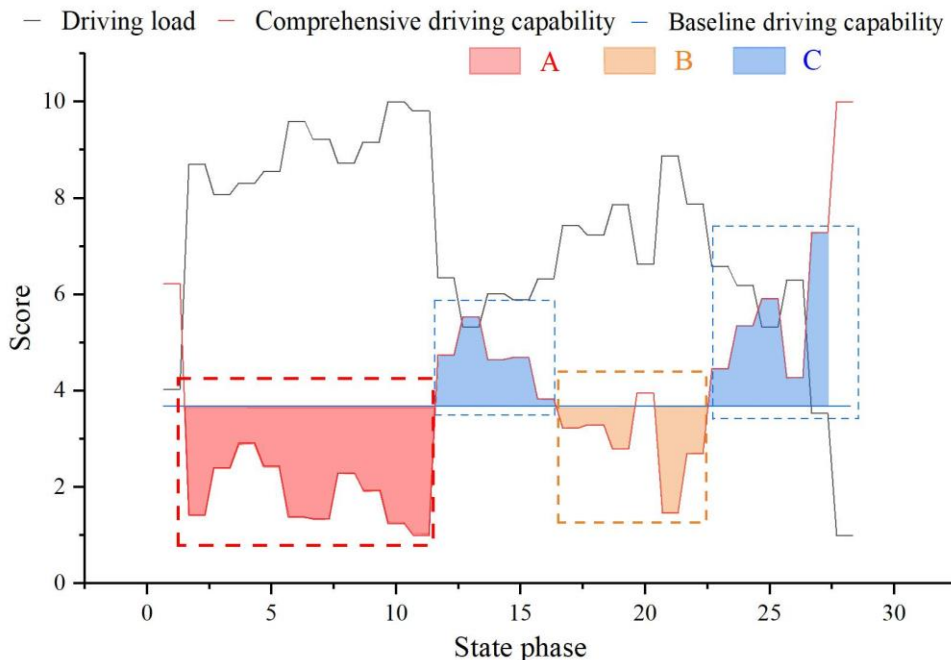


FIGURE 11. Regional division of comprehensive driving capability standards

Since driving capability is a vague concept, it is not possible to assess the upper limit of driving capability with the most objective data. However, it is possible to obtain the relative driving capability evaluation score by evaluating the relative driving capability of a continuous stage or a group of samples. The algorithm in this study could effectively obtain the distribution of the driver's comprehensive driving capability.

IV. DISCUSSION

This paper further discusses the practical implications of the ranking results of the importance of indicators obtained by the integrated weight method. From the results of the evaluation of driving capability, we analyze the characteristics of the relationship between driving load and driving capability during the operation of public transportation. Recommendations for research on the optimization of the man-computer interaction in man-computer cooperative driving are proposed.

A. EVALUATION OF METHODOLOGY

In the weighting results of the entropy weighting method and the improved ANP algorithm, the indicators with the largest weights were all eye closure, and rankings

of eye closure, yawn, and rapid deceleration were all in the top four. The weights of looking away were all smaller. The findings (see Figure 7) of the two algorithms for evaluating the comprehensive driving capability of driver No. 5 showed essentially the same trend in the two curves. In addition, the results of the Pearson correlation analysis of the two algorithms indicated a significant correlation. It showed that the two algorithms were consistent and could be fused. The weight radar graph showed that the integrated weight closed region basically covered the weight closed region of the entropy weight method and improved ANP algorithm, which verified the effectiveness of the integrated weight method. Based on the comparison of the evaluation results of the three algorithms for driver No. 5, the integrated weight method proposed in this paper fully considered the information utility of the indicators and the interaction between the indicators. The integrated weight method effectively avoided over or under evaluating the driver's comprehensive driving capability.

B. VERIFICATION OF EXPERIMENTAL RESULTS

The comprehensive driving capability of the six drivers was evaluated with the integrated weight method, and their baseline driving capability was determined. The

results showed that the comprehensive driving capability curves of the six drivers varied significantly, and the baseline driving capability value for each driver was different. The evaluation of the comprehensive driving capability of driver No. 5 showed that the driver's comprehensive driving capability score for each state stage followed a normal distribution. The trend of the comprehensive driving capability curve is consistent with the trend of the driving load curve. In particular, the comprehensive driving ability scores for stages 2, 11, and 21 were significantly higher, while the corresponding driving load scores were significantly lower. Therefore, the use of the integrated weight method can effectively evaluate the driver's comprehensive driving capability, and the results can better reflect the driver's actual driving situation.

C. EXPLORATION OF INDICATOR WEIGHTS

The top four indicators calculated by the integrated weight method were as follows: eye closure (0.241), yawn (0.210), rapid deceleration (0.186) and lane departure (0.159). Considering both the informational utility of the indicators and their interaction, eye closure, yawn, rapid deceleration and lane departure were the primary indicators to assess the driver's comprehensive driving capability under current traffic conditions, with rapid acceleration, forward collision and looking away to a lesser extent. This means that when exploring the factors that influence comprehensive driving capability in man-computer collaborative driving, research could be undertaken with these four indicators in view.

In the investigation of driving behavior characteristics, it is necessary to explore the interaction laws and causative factors between the warnings for eye closures and yawns and the other warnings to form the corresponding network system. The laws of driving behavior in man-computer cooperation situations would be explored, which provides a scientific basis for the study of man-computer cooperation control methods to meet individual needs. In the active safety prevention and control investigation of vehicles, it is necessary to explore the interaction laws and causative factors between various warning types by focusing on rapid deceleration and lane deviation, to form a network. The aim is to optimize the intelligence-assisted driving system to avoid the knock-on effect of abnormal vehicle status.

D. EXPLORATION OF THE COMPREHENSIVE DRIVING CAPABILITY ASSESSMENT

Warning data from a variety of factors, including the driver, vehicle and road traffic environment, were utilized to assess the driver's comprehensive driving capability. In the process of man-computer cooperative driving, it is possible to judge in real time whether the driver's ability meets the driving needs under the current road conditions. Thus, a man-computer interaction in the intelligent driver assistance system, such as the precise assistant control and effective switching of driving rights, could be realized.

A further analysis of the results of the driving capability evaluation showed that the lowest values of the drivers' comprehensive driving capability were mainly found in regions A and B. The driving load was significantly higher in both regional ranges, and the comprehensive driving capability was significantly lower than the baseline. These results indicated that the driver had a more significant need for driver assistance from the ADAS system. It also means that in the process of man-computer cooperative driving, the relationship between driver behavior, vehicle status, and traffic environment within the A and B regions could help to enhance driver adaptability to optimize the man-computer interaction. It is also a key point to improve the driver's comprehensive driving capability.

Furthermore, a comparative analysis of the causes and similarities of the various types of warnings (especially eye closure, yawn, rapid deceleration and lane departure) between regions A and B and region C could help optimize the active safety technology of intelligent driver assistance systems. From the distribution of driving capability scores, it can be seen that driving capability scores were mainly concentrated in the range of 1 to 6. Therefore, in addition to considering the abovementioned studies in the context of regions A and B, it is also necessary to conduct studies in the context of that interval.

V. CONCLUSIONS

A comprehensive driving capability evaluation method for man-computer cooperative driving was proposed in this paper. This proposed method aimed to provide a scientific basis for research on the precise timing of driving-right switching and allocation in the process of man-computer cooperative driving as well as to understand the timing and strength determination of assistant compensation in the ADAS system. Furthermore, an objective and effective assessment of the driver's capability could correct the driver's self-perception in real time, which is of great significance in shortening the time to take over the driving right and reduce the probability of a driving accident.

The real-time collected warning data of the bus DSMS and ADAS systems were used to calculate the indicator weights for information utility by the entropy weight method. To address the excessive subjectivity of the traditional ANP algorithm, the relative weight association rule support method was proposed to objectively determine the judgment matrix between the indicators. The improved ANP algorithm was established and used to calculate indicator weights that consider the interaction between indicators. The entropy weight method and improved ANP algorithm were combined by the integrated weight method based on the standard deviations to evaluate the driver's comprehensive driving capability under current traffic conditions in real time. The feasibility and sophistication of the integrated weight method was validated through the use of the indicator weight radar map and the comparative map of driving capability evaluation results. The comprehensive

driving capability of six drivers was evaluated using the method proposed in this study. The relationship between driver No. 5's comprehensive driving capability and driving load and baseline driving capability was analyzed to verify the validity of the evaluation results. Finally, the practical implications of the indicator importance ranking results from the integrated weight method were further discussed. The characteristics of the distribution of the driver's comprehensive driving capability in the man-computer collaborative driving process were analyzed, and relevant suggestions were made for the research of man-computer interaction optimization in man-computer collaborative driving.

In this study, we mainly used warning data to assess the comprehensive driving capability; however, the driving behaviors that triggered the system warnings have not been explored in depth. The actual reasons for the low comprehensive driving capability are not known. In future research, we will consider the suggestion presented in the discussion section of this paper to explore the relationship between driving behavior and vehicle state in the states of low comprehensive driving capability scores. This will optimize the man-computer cooperative control and improve the driver's comprehensive driving capability.

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REFERENCES

- [1] U.S., Department of Transportation, National Highway Traffic Safety Administration. Automated Driving Systems 2.0: A Vision for Safety. Washington, USA: U.S. Department of Transportation, National Highway Traffic Safety Administration, 2017.
- [2] Hu Y F, Qu T, Liu J, et al, Human-machine Cooperative Control of Intelligent Vehicle: Recent Developments and Future Perspectives[J]. *Acta Automatica Sinica*, vol.045, no.007, pp.1261-1280.
- [3] Wu C Z, Wu H R, Lyu N C, Review of control switch and safety of human-computer driving intelligent vehicle[J]. *Journal of Traffic and Transportation Engineering*, vol.18, no.6, pp.131-141, 2018.
- [4] Zhou B, Pan Q X, Feng H A, review of the research literature on the criterion of human-machine co-driving right switch[C]. *Proceedings of the 16th International Forum of Automotive Traffic Safety (INFATS 2019)*, pp.197-200, 2019.
- [5] Ghasemi A H, Jayakumar P, Gillespie R B, Shared control architectures for vehicle steering[J]. *Cognition, Technology & Work*, vol.21, pp.699-709, 2019.
- [6] Sun L, Ma Y D, Chang R S, Effects of Self-assessed Ability and Hazard Type on Young Novice Drivers' Hazard Perception[J]. *Journal of Transportation Systems Engineering and Information Technology*, vol.19, no.01, pp.232-236, 2019.
- [7] Martinussen L M, Moller M, Prato C G, Accuracy of young male drivers' self-assessments of driving skill[J]. *Transportation Research: Part F*, vol.46, pp.228-235, 2017.
- [8] Lu G Q, Zhao P Y, Wang Z J, et al, Impact of Visual Secondary Task on Young Drivers' Take-over Time in Automated Driving[J]. *China Journal of Highway and Transport*, vol.031, no.004, pp.165-171, 2018.
- [9] Zeeb K, Buchner A, Schrauf M, What determines the take-over time? An integrated model approach of driver take-over after automated driving[J]. *Accident Analysis & Prevention*, vol.78, no.5, pp.212-221, 2015.
- [10] Liu W L, Zhen L, Yang W, et al, Evaluation method of driver's capability based on analysis of vehicle states[C]. *2018SAE-China Congress proceedings*, 2018.
- [11] Sato T. Human interface based on an interaction between driver's capability and task demands[C]// *2018 IEEE International Conference on Consumer Electronics (ICCE)*. IEEE, 2018.
- [12] Wang X S, Xu X Y, et al, Assessing the relationship between self-reported driving behaviors and driver risk using a naturalistic driving study[J]. *Accident Analysis & Prevention*, vol.128, pp.8-16, 2019.
- [13] Isabelle M P, Simon M, Comparison between elderly and young drivers' performances on a driving simulator and self-assessment of their driving attitudes and mastery[J]. *Accident Analysis & Prevention*, vol.135, no.105317, 2019.
- [14] Zhou X J, Research on Driver Characteristics and Driving Capacity Real-time Evaluation [D]. *College of Automotive Engineering Chongqing University*, 2018.
- [15] Lyu A H, Zhang Y L, Wu F W, et al, An Evaluation Model for Stress Response of Drivers[J]. *Journal of Transport Information and Safety*, vol.36, no.04, pp.21-27, 2018.
- [16] John M S, Michael J F, Anuj K P, et al, Behavioral Adaptation to Advanced Driver Assistance Systems: A Literature Review[C]. *University of Michigan Transportation Research Institute / AAA Foundation for Traffic Safety*, 2016.
- [17] Shannon C E, A mathematical theory of communication[J]. *The Bell System Technical Journal*, vol.27, pp.379-423, 1948.
- [18] Liu R K, Yu L, Chen D M, Research on dependability evaluation of high-speed railway catenary based on AHP-entropy method [J]. *Journal of Railway Science and Engineering*, vol.16, no.8, pp.1882-1889, 2019.
- [19] Li S W, Yin Y N, Wang L H, Xu Y, Driving Fatigue Quantization Based on Entropy Weight Method[J]. *Journal of South China University of Technology (Natural Science Edition)*, vol.45, no.08, pp.50-56, 2017.
- [20] Wang L.F. The Theory and Algorithm of Analytic Network Process[J]. *Systems Engineering Theory & Practice*, vol.21, no.3, pp.45-50, 2001.
- [21] He C C, Wang Y M, A Review of the Analytic Network Process[J]. *Science and Technology Management Research*, vol.34, no.03, pp. 204-208+213, 2014.
- [22] Kheybari S, Rezaie F M, Farazmand H, Analytic network process: An overview of applications[J]. *Applied Mathematics and Computation*, vol.367, no.124780, 2020.
- [23] Chen J Q, Tang T, Yuan L. Management-control capability evaluation model of radio block center based on improved ANP[J]. *Journal of Traffic and Transportation Engineering*, vol.15, no.01, pp.108-118, 2015.
- [24] Uyan M, MSW landfill site selection by combining AHP with GIS for Konya, Turkey[J]. *Environmental Earth Sciences*, vol.71, no.4, pp. 1629-1639, 2014.



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