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Abstract: The content and density of road traffic signs affect the driving behaviour of drivers and the smoothness of urban traffic. There is a lack of quantitative research methods on the current information threshold of traffic signs. In order to quantitatively classify the informativeness threshold of traffic signs and better explore the reasonableness of traffic sign setting, this paper designed a real-vehicle experiment, adopted the principal component analysis (PCA) method, conducted multi-dimensional analysis of pupil area, fixation intensity, heart rate change rate and heart rate variability, quantified the traffic sign information by using the information entropy theory and introduced the comfort index S , and established regression relations. Driving visual comfort was quantitatively classified into five levels, and it was indicated that the traffic sign information density should be less than 0.373 bits/m and maximum should not exceed 0.507 bits/m.

Keywords: urban road; traffic sign; real vehicle test; visual comfort; amount of information; information density; traffic safety; pupil area; heart rate.

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1 Introduction

With the development of urbanisation in the world, the land area of the city has been expanded continuously, and the huge land area needs to build roads to connect the different distribution and functions of different areas. The number of roads is increasing, the length is getting longer and longer, and there are various development concepts and rules for road construction in different cities. However, during the extended periods of construction and operation of urban roads, there has been a tendency among builders to focus predominantly on road layout, often neglecting a comprehensive understanding of traffic signs. This oversight results in an overload of traffic sign information along roads, which in turn increases the cognitive burden on drivers (Yang et al., 2021). Throughout the driving process, drivers rely heavily on visual cues to gather and process road information necessary for maintaining optimal driving conditions. Traffic signs serve as the primary means of disseminating this information (Du et al., 2023). When there is either insufficient or excessive information presented on traffic signs, it can lead to heightened psychological strain and increased driving fatigue (Liu and Deng, 2021).

During the driving process, drivers experience a specific psychological load. A driver's working state can be characterised by their driving load, which must remain within a suitable range to ensure driving safety. The driving load is closely linked to the visual comfort index (Kang et al., 2020; Zang et al., 2023). A higher level of visual psychological load correlates with lower driving comfort, whereas a lower level of visual psychological load corresponds to higher driving comfort. On urban roads, drivers frequently engage in tasks such as maintaining lane position, making turns, and changing lanes, all of which are crucial for driving safety.

Various methods are employed to investigate driving load and comfort, categorised into subjective index assessments, driving operation evaluations, and psychological index assessments, each with distinct strengths and limitations (Meng et al., 2021). We assert that the psychological index assessment method, capable of capturing real-time driver states, is more scientifically robust and has seen widespread application, as supported by existing research (Zhang et al., 2022; Fatmi and Habib, 2019; Babić et al., 2022).

The information carried on traffic signs can provide drivers with road information in a timely manner. For urban roads, drivers are usually informed in advance of the path information of each road direction in the form of wayfinding signs, or early warning of height limits, speed limits, school zones and other unexpected information. Traffic signs offer crucial guidance for drivers to navigate correctly and make informed driving decisions. Well-placed traffic signs contribute to drivers feeling safe and at ease, whereas poorly positioned signs can lead to discomfort and increased effort (Zheng et al., 2021). Thus, studying the optimal density of road traffic signs from the perspective of drivers' visual comfort is an effective approach to enhancing both safety and comfort.

In this study, an urban road served as the research setting where drivers' psychological parameters were gathered through experimental methods. Collected data required validation, leading to the proposal of a model for driving visual psychological load and an evaluation method for visual comfort. Additionally, a method to quantify the information conveyed by road traffic signs was introduced, investigating the relationship between this information and drivers' visual comfort.

The study proposes a driving visual psychological load model and a visual comfort evaluation method, along with a quantification method for traffic sign information. It also explores the correlation between traffic sign information and drivers' visual comfort.

The aim of this paper is to investigate the visual psychological load model for urban roads and how traffic sign information affects drivers' visual comfort, ultimately guiding the rational layout of traffic signs. Using principal component analysis (PCA), the study performs a multidimensional fusion of driving comfort indicators, including pupil area, fixation intensity, heart rate change rate, and heart rate variability. Additionally, it applies information entropy theory to quantify the informational content of these indicators.

2 Literature review

When driving on urban roads, drivers are constantly exposed to various scenes outside the vehicle, with traffic signs being a significant focus of their attention (Schnell et al., 2024). These signs continuously provide crucial information, especially in complex driving environments such as intersections or dense traffic conditions. As drivers process this information, they experience a certain psychological load that impacts both the safety and comfort of their driving experience.

In the realm of traffic signs, experts and scholars have focused on quantifying the information drivers receive and determining optimal sign density (Du et al., 2023; Liu and Deng, 2021; Zheng et al., 2021). It's important to note that the psychological load examined in this study specifically pertains to the cognitive burden drivers experience when processing traffic sign information within a limited timeframe, distinct from the broader concept of driving fatigue.

Through real driving experiments and driving simulator experiments, a series of biopsychological indicators of drivers can be obtained to study the driver's workload and

driving comfort during driving. Scholars have been exploring the relationship between driver comfort and changes in road conditions through a number of physiological changes such as eye movement trajectories, changes in brain wave activity in different frequency bands, and changes in heart rate (Mohamad et al., 2023; Ju et al., 2023).

Comfort, whether experienced during driving or other activities, is a subjective aspect of human perception. Some studies suggest that comfort is a psychological sensation that arises in a particular environment (Medeiros et al., 2023). Some studies also posit that comfort is a bodily response triggered by the surrounding environment (Haghani et al., 2021; Xu et al., 2020). In the context of driving, visual comfort pertains to the degree of psychological satisfaction derived from observing engaging elements outside the vehicle.

The visual comfort of drivers is influenced by various factors, including road landscape, terrain conditions, road types, and information provided by traffic signs. Scholars generally agree that when the driver's workload becomes excessive, the pupil size will change rapidly, the heart rate will increase, and the fixation time will be extended, indicating a decrease in driving comfort (Min and Cai, 2020; Meng et al., 2021). Understanding the mechanisms through which road environments and visual comfort influence each other has become a prominent area of study among scholars.

EEG and ECG are the parameters most commonly used for driver characterisation, Fatigue or other specific driving states can be analysed by using either of the two types of data (Wang et al., 2023). Different frequency bands of brainwaves are usually selected for screening when analysing different types of driving states, e.g., changes in alpha waves can be used to characterise driver agitation, which will be attenuated or absent when the driver is angry or panicked (Affanni et al., 2022). Heart rate and heart rate variability are commonly used to characterise driver tension while driving, with heart rate increasing sensitively and rapidly in response to increasing cognitive workload (Tselentis and Papadimitriou, 2023).

The eye movement index is another major parameter used to assess the driver's attention allocation during driving. Pupil area, rate of change of pupil area, fixation area and fixation duration can reflect different driving conditions (Felbel et al., 2022; Azimian et al., 2021). In general, the rate of change of pupil area can reflect the driver's nervousness when facing changes in the driving environment, and the larger the rate is, the more it can indicate that the driver has entered into a state of nervousness. The distribution of the fixation area can reflect the driver's attention distribution, the scanning and fixation behaviour can analyse whether the driver's observation of an object or scene is conscious or unconscious. Too short unconscious scanning behaviour means that the driver's acquisition of information is not effective enough, while too long conscious fixation behaviour may lead to the driver investing too much attention and cause driving distraction.

Some other types of indicators can also respond to the driver's driving state, people in different psychological and physiological state, the skin conductivity will change, skin conductivity coefficient can be used to determine whether the driver is facing some of the situation into a state of tension or fatigue (Amidei et al., 2022, 2023); Salivary enzymes and blood composition analysis are commonly used to study the physical state of drivers after taking alcohol, marijuana or other psychoactive stimulants, in order to explore the changes in driving ability after taking specific substances (Alexandrescu et al., 2024; Trojan et al., 2022).

The driver's recognition time can reflect their mental load, and the 61% of the driver's recognition time can be explained by the traffic sign information quantity, the

increase in the amount of sign information means that drivers need to recognise more information content, requiring more time and effort to make judgements and actions (Han et al., 2024; Gjorgjievski et al., 2021). At a fixed speed, an increase in recognition time means an increase in recognition distance, which affects driver safety.

In a summary, multiple psychophysiological parameters can be used to characterise the driving load of drivers. There is a clear relationship between driving psychological load and driving comfort. Driving comfort is closely related to the driver's overall perception of the environment and can more directly describe the driving experience. Additionally, employing drivers' psychological indicators allows for a more quantitative assessment. Currently, research primarily examines driving comfort through drivers' psychological parameters, with less emphasis on the attention devoted to traffic signs during driving. Nevertheless, traffic signs remain crucial for drivers throughout their journey.

Existing research generally agrees on utilising drivers' psychological indicators to measure driving comfort, alongside methods for assessing the informational content of traffic signs. However, research on visual comfort during driving and reasonable thresholds for traffic signs on urban roads is currently at a preliminary stage of development.

3 Real vehicle test

3.1 Test design

This study used a method in which a subject was tested in a real car on an urban road set up with a number of different traffic signs. While driving, the driving subjects' eye movements, heart rate, and other psychological data were measured by a special test instrument, and the data were then analysed. As it involved the participation of the subjects prior to the experiment, all subjects were aware of the purpose of this test and agreed to the use of the test data for research purposes.

Three main steps were designed into this experiment:

- 1 selecting the test road section
- 2 determining the subjects and test vehicle
- 3 installing the test instrument in the vehicle

After the completion of the real vehicle test, the data were analysed.

In order to obtain more test data and to facilitate the exploration of regularities, each subject drove back and forth on the test section twice. The actual driving arrangement was: the subjects were sequentially numbered as 1, 2..... 0.10 and the experiment was conducted according to the driving numbers.

First, subject 1 performed the test while subject 2 stayed in the car. After reaching the end of the test section, Driver 1 rested for about 5 min, then Driver 2 drove to the beginning of the test section, and so on until the first round of testing was completed. Afterwards, subject 1 and subject 2 exchanged driving directions, and subject 2 set off for the end of the road section and subject 1 returned to the beginning of the road section to complete the second round of testing of these two subjects. Third, the forward and

backward directions were repeated until the second round of testing was completed. Thus, all subject drivers were tested in both directions and completed the test.

3.1.1 Test road section

The experimental road section, which fully met the relevant current Chinese standards after reviewing the data from the site investigation, is located in Nanchang City, Jiangxi Province, China. Factors other than traffic signs, such as roadside landscape, road width, traffic volume, etc., did not change much and met the test requirements. According to the field measurements and design information, the length of the test road is about 5 km and the design speed is 60 km per hour. Bi-directional four-lane road and each lane is 3.5 m wide. The traffic flow on the selected road sections was purposely kept at a low level to minimise the driving interference from other vehicles and to facilitate the subjects to travel freely, thus maintaining the integrity of the test results.

3.1.2 Subjects and test vehicle

During the test, it is important to minimise the influence of individual differences among drivers on the test results (Lv et al., 2022; Wang and Zhou, 2021; Himmels et al., 2022). To fulfil this criterion, a specific number of drivers is required.

Ideally, the minimum sample size for an experiment is given by $N = \left(\frac{\sigma K}{E}\right)^2$, where N is the required sample size, σ is the standard deviation of the population, assuming that the standard deviation of the speed is 5–10 km/h, K is a constant, is the statistic at the confidence level when the confidence level is equal to 95%, $K = 1.96$, and E is the allowable error.

In the experiment designed in this paper, the allowable error of the running speed was set to 5 km/h. In order to ensure that the data obtained from this experiment is sufficiently reliable and valid, the minimum sample size N should be greater than 4. Considering the site, time and cost constraints of the actual test, 10 volunteers were selected for the experiment in this paper to collect as much sample data as possible.

This test did not discuss driving behaviour in terms of drivers' personality traits, but subjects were selected to cover as many categories of people as possible to make the sample reliably representative. Considering that drivers have different years of driving experience, questionnaire was conducted to find out how often and how many years the subjects had been driving. The subjects consisted of six males and four females, with half of the total number of subjects with less than five years of driving experience, and seven subjects drove at least four times a week. From this, it can be seen that the selected driving subjects in the experiment have very good representativeness.

Ten drivers with normal or corrected vision, including six males and four females, were selected for the test. The drivers selected for the test were between 20 and 50 years of age and were free from any negative habits. Their demographics and traits align with those typical of their region. All drivers were unfamiliar with the road sections on which the tests were conducted. Considering the inherent risks of driving, the subjects all held valid driving licences and had at least 3 years of driving experience. In addition, they were asked to maintain a healthy physical condition, eat a normal diet, get adequate rest, and ensure that their living conditions were conducive to safe driving prior to the test.

The test vehicle was a Buick commercial vehicle with the subject sitting in the driver's seat. A test participant in the car was responsible for checking the test instruments at any given time. Test instruments were installed in the test vehicle.

3.1.3 Test instruments

An eye-tracker called Dikablis was used to collect eye movement data from the driver, equipped with a camera to collect environmental data inside and outside the vehicle at a sampling rate of 50 Hz. A bio-signal recorder named Varioport was used to collect ECG data from the driver with a sampling rate of 100 Hz. The data to be studied in this paper, pupil area, fixation behaviour and heart rate, were obtained through these two devices.

3.2 Test procedure

Drivers were assembled at the start of the test at the beginning of the road section and tested for their physical condition to ensure that they were in a healthy and energetic state. The eye-tracking and ECG recorders were then distributed and fitted to the drivers after being commissioned. After checking, the test started.

The driver (No. 1) drove the vehicle from the start of the road section A to the end of the road section B. The staff accompanying the vehicle operated the test equipment and recorded the driving time as well as the corresponding visual and heart rate indicators (Figure 1). After the driver (No. 1) arrived at the end of the test section B, another driver (No. 2) took a 5-minute break and then returned to the original route to complete the driving cycle. The next group of subjects then performed the same procedure until all drivers had completed the test.

Figure 1 Diagram of eye-tracker wearing situation (left) and vehicle interior (right) schematic (see online version for colours)



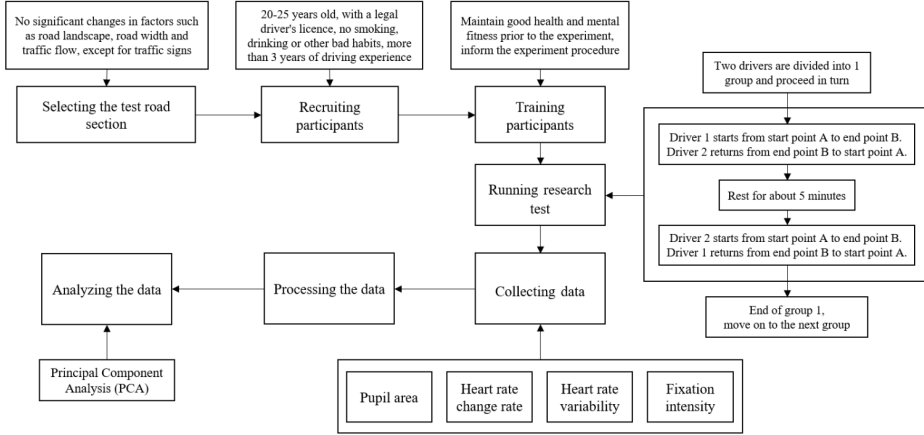
Figure 2 is the architecture diagram of the whole experiment, in order to facilitate the reader to have a more concrete understanding of the experimental procedure in this paper.

3.3 Multi-characteristic parameter research

There is a rich diversity of indicators of driving comfort in the studies available today (Karageorghis et al., 2022; Zheng et al., 2024; Ge et al., 2023; Feng et al., 2021). The effects of the age and gender of the subjects were not considered during the data analysis

in this paper. Based on the purpose of the experiment and the collected data, four psychological indicators – pupil area change rate, fixation intensity, heart rate change rate and heart rate variability – were selected for comprehensive analysis.

Figure 2 Architecture diagram of the experiment



A total of approximately 600,000 eye movement data and 1.2 million heart rate data were collected from ten subject drivers. A clustering method was used to test the validity of the data. Data that exceeded the upper 20% of the mean were excluded because of the relative stability of the drivers' psychological responses during the test. In addition, data from the start and finish sections of the test drivers were excluded, leaving 428,040 eye movement data and 882,720 heart rate data for the study. The amount of data was sufficient for this study. Subsequent analyses were based on the valid data and examined the correlation between the test data and the traffic signs.

3.3.1 Change rate of pupil area

The rate of change of the pupil area (Chen et al., 2022) can be utilised as an indicator for evaluating psychological responses and driving comfort. The rate of change in the pupil area is defined as equation (1):

$$R_r = \left| \frac{S_2 - S_1}{S_1} \right| \times 100\% \quad (1)$$

where R_r is the change rate of the pupil area of the driver, S_2 is the pupil area during driving, S_1 is the pupil area before driving.

3.3.2 Fixation intensity

Fixation intensity is an indication of a driver's attention to traffic signs and efficiency in processing environmentally relevant information at a given speed, which is the product of the average fixation time of a single fixation point and the average number of fixations per unit of time of the driving section (Han et al., 2023), which can be expressed as equation (2):

$$a = T_a N_a \quad (2)$$

where a is the driver's fixation intensity, T_a is the average fixation time of a single fixation point and the unit is second(s), N_a is the average number of fixations per unit time and the unit is times/s.

3.3.3 Change rate of heartbeat

The change rate of the heartbeat can reflect the driver's feelings of oppression and impatience (Fine et al., 2022). At the same time, a driver with a heart rate variability of more than 20% will experience an increase in psychological tension and a corresponding decrease in driving comfort. To accurately analyse driver heartbeat changes at a certain time or period, a quantitative approach is used. The calculation of the change rate of heartbeat N_i is as equation (3):

$$N_i = \left| \frac{HR_i - HR_0}{HR_0} \right| \times 100\% \quad (3)$$

where N_i is the change rate of the heartbeat of the driver, HR_i is the heartbeat, and HR_0 is the average heartbeat per unit time.

3.3.4 Heart rate variability

Heart rate variability, namely, the standard deviation of the heartbeat interval, is a commonly used temporal analysis indicator (Yang et al., 2021). The parameter SDNN, i.e., standard deviation of NN intervals, is chosen as the main indicator to characterise drivers' heart rate variability (Persson et al., 2020; Rostamzadeh et al., 2024).

In this study, the SDNN was used to describe the magnitude of variability in the driver's heart rate. The SDNN of the driver's heart rate variability is calculated every 30s. The SDNN calculation formula is as equation (4):

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (r_i - \bar{r})^2} \quad (4)$$

where SDNN is the deviation of the NN intervals, N is the total number of R waves in this period, r_i is the i th NN interval size, \bar{r} is the average NN interval of a time range.

3.4 Multi-feature fusion of driving visual comfort

3.4.1 Correlation analysis of characteristic parameters

The significance of normal distribution of the four types of parameters in Section 3.3 was examined using the Kolmogorov-Smirnov(K-S) test, which has the advantage of being easy to compute and fast to run, and does not require additional processing of the data. The results of the test were that all four types of parameters were suitable for normal distribution analysis and their respective significance levels were greater than 0.05 as shown in Table 1.

Table 1 Test results of normality hypothesis for each data

<i>Null hypothesis</i>	<i>Significance level</i>	<i>Decision</i>
The distribution of the change rate of pupil area was found to be normal, with a mean of 8.11 and a standard deviation of 1.92	0.075	Keep the null hypothesis
The distribution of fixation intensity was found to be normal, with a mean of 6.59 and a standard deviation of 0.43	0.061	Keep the null hypothesis
The distribution of change rate of heartbeat was found to be normal, with a mean of 79.916 and a standard deviation of 7.745	0.099	Keep the null hypothesis
The distribution of heart rate variability was found to be normal, with a mean of 65.16 and a standard deviation of 4.32	0.089	Keep the null hypothesis

The correlation between the above four parameters was examined using the Pearson's correlation test. The advantage of Pearson's correlation test is that it has a very wide range of applications and the calculation method is simple and easy to understand, but the method requires that the variables it tests need to obey a normal distribution, and it may not be applicable to non-normally distributed data (Wang et al., 2020). The analysis was conducted to explore the correlation between the drivers' visual comfort indices. The results are presented in Table 2.

Table 2 Correlation analysis of visual comfort index

<i>Visual comfort index</i>	<i>Pearson analysis</i>	<i>Change rate of pupil area</i>	<i>Fixation intensity</i>	<i>Change rate of heartbeat</i>	<i>Heart rate variability</i>
Change rate of pupil area	Pearson correlation	1.000			
	Significance (bilateral)				
Fixation intensity	Pearson correlation	0.646	1.000		
	Significance (bilateral)	0.000			
Change rate of heartbeat	Pearson correlation	0.395	0.337	1.000	
	Significance (bilateral)	0.000	0.000		
Heart rate variability	Pearson correlation	-0.296	-0.241	-0.547	1.000
	Significance (bilateral)	0.002	0.013	0.000	

The test results in Table 2 show that the four types of parameters have significant correlations of varying strengths, indicating the existence of varying degrees of correlation between them, which can be analysed by subsequent extraction of common feature data.

3.4.2 Calculation model of visual load

Principal component analysis is a data processing method that analyses parameters to extract common elements from sample variables. It has the advantage of integrating multiple indicators into one or fewer indicators, and compounding indicators of multiple dimensions to reduce the difficulty of data analysis (McManus et al., 2024). The suitability and relevance of the sample was confirmed by the Kaiser-Meyer-Olkin (KMO)

test and Bartlett’s test of sphericity, which are important steps in the PCA approach. The KMO test is a statistic used to compare the simple correlation coefficients and partial correlation coefficients between variables, which is mainly used in factor analysis of multivariate statistics. The value of KMO test is between 0 and 1, and the closer to 1 means the stronger the correlation between the variables, the more suitable for factor analysis. When the value of the KMO test is more than 0.5, it indicates that the variables can be analysed in factor analysis.

The Bartlett’s test of sphericity is also a statistical method for testing the degree of correlation between variables, and is often used in conjunction with the KMO test to more rigorously determine the suitability of a variable for use in factor analysis. If the probability of significance of the Bartlett’s test of sphericity is less than 0.05 at the same time with a KMO value greater than 0.5, then the data is suitable for factor analysis.

The results of the KMO test and Bartlett’s test of sphericity for the four parameters in Section 3.3 are shown in Table 3, where the significant probability of the Bartlett’s test of sphericity is 0.000 and the value of the KMO test is greater than 0.5, which suggests that the four parameters can be subjected to factor analysis.

Table 3 Results of the KMO test and Bartlett’s test of sphericity

Sampling enough for Kaiser-Meyer-Olkin metric.		0.642
Bartlett test of sphericity	Approximate chi-square	111.129
	df	6
	Sig.	0.000

For the next step of data analysis, the experimental data were standardised using the Z-score standardisation method by identifying common factors. Z-score standardisation, also known as standard deviation standardisation, is a commonly used data processing method that converts raw data into standardised Z-score scores by calculating the standard deviation and mean. This approach has a wide range of applicability and is able to convert different orders of magnitude of data into a uniformly measured Z-Score for comparison. Table 4 demonstrates the variance explained for each factor.

Table 4 Interpret total variances

Index	Initial eigenvalue			Extract the sum of squares		
	Total	Variance (%)	Accumulation (%)	Total	Variance (%)	Accumulation (%)
1	2.237	55.930	55.930	2.237	55.930	55.930
2	0.971	24.281	80.211	0.971	24.281	80.211
3	0.442	11.042	91.253			
4	0.350	8.474	100.000			

In order to determine the exact number of common factors, the amount of information about the variables covered by the factors was analysed using the rubble test. Most of the information of the original variable can be expressed by the two common factors, and Table 5 demonstrates the loading matrix of these two factors. The matrix illustrates the degree of influence of these two common factors on the four different kinds of biopsychological parameters when it comes to the four different kinds of

biopsychological parameters, through which the relationship between each parameter and the common factors can be obtained as shown in equation (5):

$$\tilde{X}_1 = 0.798F_1 + 0.420F_2 + \varepsilon_i \quad (5)$$

In equation (5), \tilde{X}_1 is the change rate of the pupil area after standardisation, F_1 is the common factor 1, and F_2 is the common factor 2, which is the special factor \tilde{X}_1 .

Table 5 Factor loading matrix

<i>Factors</i>	<i>Loading score</i>	
	<i>1</i>	<i>2</i>
Change rate of pupil area	0.798	0.42
Fixation intensity	0.755	0.512
Change rate of heartbeat	0.759	-0.421
Heart rate variability	-0.674	0.597

Using the variance-maximising orthogonal rotation method, the factors are rotated and adjusted under the condition of ensuring that they are orthogonal to each other, so that the variance difference of each factor is maximised, thus better explaining the extracted factors. Table 6 demonstrates the component matrices of the factors after rotation.

Table 6 Component matrix after factor rotation

<i>Index</i>	<i>Ingredient</i>	
	<i>1</i>	<i>2</i>
Change rate of pupil area	0.872	0.230
Fixation intensity	0.903	0.133
Change rate of heartbeat	0.275	0.823
Heart rate variability	-0.094	-0.895

The pupil area variability and fixation intensity can be classified into the category of ‘eye movement load factor’, while heart rate variability and heart rate variability can be classified into the category of ‘heart rate load factor’ to study driver comfort from two perspectives.

The linear relationship between each eigen parameter and the common factor can be obtained from the component matrix in Table 6, thus expressing the common factor in terms of the eigen parameters. The component coefficient matrices of the eye movement load factor and heart rate load factor shown in Table 7 were obtained using regression estimation. Therefore, the expression of the score coefficient of the eye movement load factor and heartbeat load factor can be obtained using each characteristic parameter, that is, F_1 and F_2 . This is shown in equation (6).

$$\begin{aligned} F_1 &= 0.555\tilde{x}_1 + 0.605\tilde{x}_2 - 0.043\tilde{x}_3 + 0.193\tilde{x}_4, \\ F_2 &= -0.078\tilde{x}_1 - 0.161\tilde{x}_2 + 0.549\tilde{x}_3 - 0.656\tilde{x}_4 \end{aligned} \quad (6)$$

where F_1 is the eye movement load factor, F_2 is the heartbeat load factor, $\tilde{x}_1, \tilde{x}_2, \tilde{x}_3, \tilde{x}_4$ are the rate of change of pupil area, fixation intensity, rate of change of heart rate, and heart rate variability after standardisation treatment, respectively.

Table 7 Score coefficient matrix of each component

Index	Ingredient	
	1	2
Change rate of pupil area	0.555	-0.078
Fixation intensity	0.605	-0.161
Change rate of heartbeat	-0.043	0.549
Heart rate variability	0.193	-0.656

Equation (7) is the model for calculating the values of visual cardio-physiological loads of drivers, and the relationship between eye movement loads, heart rate loads, and visual psychological loads of drivers was linearly fitted by factor component coefficients and variance contributions.

$$S = \frac{55.93F_1 + 24.28F_2}{80.21} = 0.697F_1 + 0.303F_2 \tag{7}$$

where S is the level of driving visual psychological loads.

This model provides a more accurate estimate of a driver’s actual mental load due to the combined consideration of the commonality of the driver’s eye movement characteristics and heart rate characteristics. As all parameters are normally distributed data that have been standardised when performing the calculation of the upper level of visual psychophysiological load, the level of visual mental load should also conform to a normal distribution. To confirm this conclusion, a K-S test was performed on the visual mental load level, which showed a significance level of 0.156, which is consistent with normal distribution.

3.4.3 Classification of visual comfort level

The significant value of the normality test result after analysing the collected visual psychological data is 0.156 which is greater than 0.05 and indicates that the level of visual mental load is tested for normality. For a set of random data obeying a normal distribution, the closer the data in it is to the mean the more likely it is to occur, and if a data value deviates from the mean by three standard deviations, the probability of it occurring will be less than 0.3% (Meng et al., 2023). The probability of occurrence of data two standard deviations from the mean is 95.4%, and the probability of occurrence of data one standard deviation from the mean is 68.2%.

The range of deviations of values compared to the mean within three standard deviation sizes was selected as the possible range of visual mental load for drivers. According to the different ranges of deviation, the visual comfort level was divided into $x \pm \sigma, x \pm 2\sigma, x \pm 3\sigma$ as boundary points (Meng et al., 2024).

Table 8 illustrates the five driving visual comfort tiers based on different ranges of psychological load.

Table 8 Classification of driving visual comfort

<i>Driving visual comfort level</i>	<i>Range of psychological load</i>
Very comfortable	$-2.289 \leq S < -1.526$
More comfortable	$-1.526 \leq S < -0.763$
Comfortable	$-0.763 \leq S \leq 0.763$
Uncomfortable	$0.763 < S \leq 1.526$
Very uncomfortable	$1.526 < S \leq 2.289$

4 Traffic sign information

4.1 Quantification method of urban road traffic sign information

Shannon's information entropy theory is the basis for most of the information calculation methods of urban road traffic engineering facilities. Shannon called the amount of information contained in the information source as information entropy and used it to describe the average size of event information. The information quantity is an effective tool for measuring and determining the amount of information about a location object in bits. When a random variable has a certain value, the logarithm of the reciprocal of its probability is the amount of information. The amount of information contained in an object is negatively correlated with its probability of occurrence, which means that if its probability of occurrence is greater, then its uncertainty is smaller, and the amount of information it contains is also smaller (Wen et al., 2021). The sign information quantity calculation model in this paper is based on the information entropy theory, counting the probability of occurrence of each element in the road traffic sign, calculating the information quantity of each element type, and finally getting the total information quantity of the sign.

I_i is the amount of information, $p(x_i)$ is the probability of the occurrence of event x_i , and the mathematical expression for the amount of information is shown in equation (8).

$$I_i = -\log_2 p(x_i) \quad (8)$$

The information entropy, obtained through the sum of the product of each state's probability of occurrence and its amount of information, is a measure of the information contained in the source, and the information expected to be contained in the event. The calculation based on the information theory of Shannon for the amount of information in traffic engineering facilities is shown in equation (9).

$$H(X) = -\sum_{i=1}^n p(x_i) \log_2 p(x_i) \quad (9)$$

where X is the traffic engineering facility event, $H(X)$ is the information amount (bits), N is the total number of possible states of event X , X_i is the i th state of the event, $P(x_i)$ is the probability of occurrence of event x_i .

The types of traffic signs on Chinese urban roads are mainly wayfinding and warning signs, and the elements in the signs contain various types of symbols such as Chinese

characters, English letters, numbers, colours and arrows (Zhao et al., 2022; Du et al., 2022). When the road conditions are good, traffic signs are the focus of attention for drivers.

It is assumed that events in each different state have the same probability of occurring; that is, in this process of traffic sign informativeness calculation, all kinds of elemental information on a sign produce visual stimuli to the driver with equal probability. Then, the probability of occurrence of elements of sign information of counting type is $P(x_i) = 1/n$ and that of length type is $P(x_i) = M/n$. M is the length of an element's information type and n is the calculated length of all elements.

According to the calculation equation for the information amount of traffic signs on an urban road, the calculation of the single information number of counting-type elements can be simplified as equation (10):

$$H(x_i) = \log_2 n \quad (10)$$

The information amount of each single element of the traffic signs can be obtained according to the above equation, and the calculation process is listed.

- 1 *Chinese characters*: About 99.48% of the Chinese language scenarios can be covered by the 3500 characters in the List of Commonly Used Characters in Modern Chinese. The amount of information contained in each Chinese character is $H(X_1) = \log_2 3500 = 11.77\text{bits}$.
- 2 *English letters*: The amount of information contained in each of the 26 letters of the English alphabet covering their case forms is $H(X_2) = \log_2 52 = 5.70\text{bits}$.
- 3 *Arabic numerals*: The amount of information contained in each of the ten Arabic numerals is $H(X_3) = \log_2 10 = 3.32\text{bits}$.
- 4 *Colour*: Black, white, green, blue, red and yellow are the main colours used for road traffic signs, and with the addition of brown, which is used for tourist area signs, the amount of information contained in each colour is $H(x_4) = \log_2 7 = 2.81\text{bits}$.
- 5 *Directional arrows*: Approximately 40 types of directional arrows are used on the traffic signs of urban roads, and each arrow contains $H(x_5) = \log_2 40 = 5.32\text{bits}$.
- 6 *Symbols*: When carrying out the calculation of the information quantity of sign symbol elements, it can be adjusted according to the actual situation of the local city. Due to the flat terrain, the sign symbols on urban roads in Nanchang City are basically based on wayfinding information, such as tunnels, narrow roads and other special terrain warning symbols are relatively few. According to statistics, there are about 60 kinds of symbols for traffic signs on urban roads, each symbol contains information $H(x_6) = \log_2 60 = 5.91\text{bits}$.
- 7 *Shape*: There are six commonly used shapes of traffic signs on urban roads: triangle, square, circle, rectangle, octagon, and pentagonal. The amount of information contained in each shape is $H(x_7) = \log_2 6 = 2.59\text{bits}$.

The amount of information contained in each traffic sign is obtained by integrating the amount of information contained in all of its elements, by means of equation (11):

$$H(X) = \sum(H(x_i), n) \quad (11)$$

where $H(X)$ is the information amount of traffic signs on urban roads (bits), $H(x_i)$ is the amount of information contained in a single element (bits), N is the number of elements on the traffic sign.







As the distribution of traffic signs in the road is not uniform, and the amount of information carried by each traffic sign is not the same, the traffic sign information density is defined as the amount of information that can be transmitted by traffic signs to drivers per unit of road mileage (Bobermin et al., 2021; de Frutos et al., 2023), which is calculated by equation (12):

$$\rho(X) = \frac{H_L(x_i) + H_S(x_i)}{2S} \tag{12}$$

where $\rho(X)$ is the information density of urban road traffic signs (bits/km), $H_L(x_i)$ and $H_S(x_i)$ are the information amounts of traffic signs on both sides of the road (bits), S is the length of the urban road (km).

Table 9 shows six actual road traffic signs that appeared in the real vehicle experiments to help readers understand the process of calculating the total information content of road traffic signs in this paper in a more concrete form.

Table 9 Amount of information for some traffic signs (see online version for colours)

Type of traffic signs	Each element in traffic sign							Amount of information (bits)
	Chinese characters	English letters	Arabic Number	Colour	Arrows	Symbol	Shape	
	0	0	0	2	0	2	2	22.62
	0	0	0	2	0	2	2	22.62
	0	0	0	2	1	0	2	16.12
	0	0	2	3	0	0	2	20.25
	0	1	2	3	0	0	3	28.54
	0	1	2	3	0	1	3	34.45

4.2 Analysis of traffic sign information and visual

In this section, four types of parameters, namely, rate of change of pupil area, fixation intensity, rate of change of heart rate, and heart rate variability, were calculated and analysed. Then Pearson's correlation test was performed between these four types of parameters and traffic engineering information volume. The results of the test are shown in Table 10.

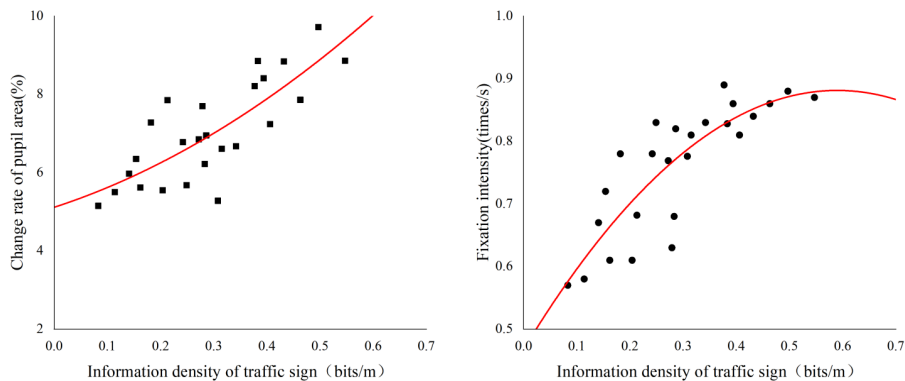
Table 10 Parameters of traffic sign information density and visual comfort

<i>Correlation analysis with information density</i>	<i>Change rate of pupil area</i>	<i>Fixation intensity</i>	<i>Change rate of heartbeat</i>	<i>Heart rate variability</i>
Pearson correlation	0.717	0.763	0.631	-0.576
Significance (bilateral)	0.001	0.000	0.002	0.006

The magnitude of the values of Pearson correlation in the Table 10 represents the correlation between the two parameters, and the positive or negative values represent whether the two parameters are positively or negatively correlated with each other. The magnitude of the values of Pearson's correlation in the table represents the correlation between the two parameters, and the positive or negative values represent whether the two parameters are positively or negatively correlated with each other. That is, there is a medium-strength negative correlation between the information density of traffic signs and heart rate variability.

Figure 3 illustrates the variation of eye movement parameters under conditions of increased traffic sign information. When travelling on road sections with low traffic information density, the rate of change of the driver's pupil area as well as fixation intensity were at a relatively low level, and then increased with increasing information density. The trend of increasing fixation intensity levelled off after the information density of the traffic facility reached a density of 0.4 bits/m.

Figure 3 Relationship between eye movement load factors and information density of traffic sign (see online version for colours)

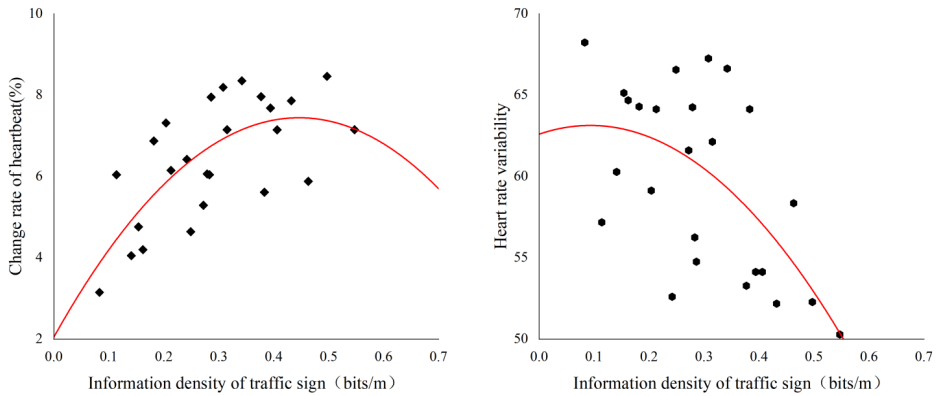


The increased information density of transport sign means that drivers need to access and process more information in the same amount of time, which results in greater driving loads. The increasing rate of change of pupil area indicates that a higher information

density means a greater and more significant driving load for the driver. The intensity of fixation increased and then levelled off because drivers have a limited amount of time to allocate to traffic sign, and too much fixation time will reduce the acquisition of direct information such as the movement of other vehicles in the road.

Figure 4 shows the variation of driver heart rate loading parameters as the density of traffic sign information increases. The rate of change of drivers' heart rate also increases gradually when the density of sign information volume increases, and the trend of increase is no longer obvious after the traffic sign information volume reaches 0.4 bits/m. It can be assumed that an increase in the amount of sign information creates a significant tension in the driver, and the increase in tension is no longer significant after the amount of sign information reaches 0.4 bits/m.

Figure 4 Relationship between heartbeat load factors and information density of traffic sign (see online version for colours)



The variability of the driver's heart rate shows a trend of slow change followed by a rapid decrease. It can be assumed that there is a certain lag in the time of change of the driver's state to the change of the density of the sign information, but the change is rapid. If the amount of sign information is below 0.3 bits/m, the driver may not feel obvious discomfort. When the amount of sign information exceeds 0.4 bits/m, the driver will feel a certain degree of discomfort, and the nervousness will reach a more obvious peak at a density of information of 0.4 bits/m.

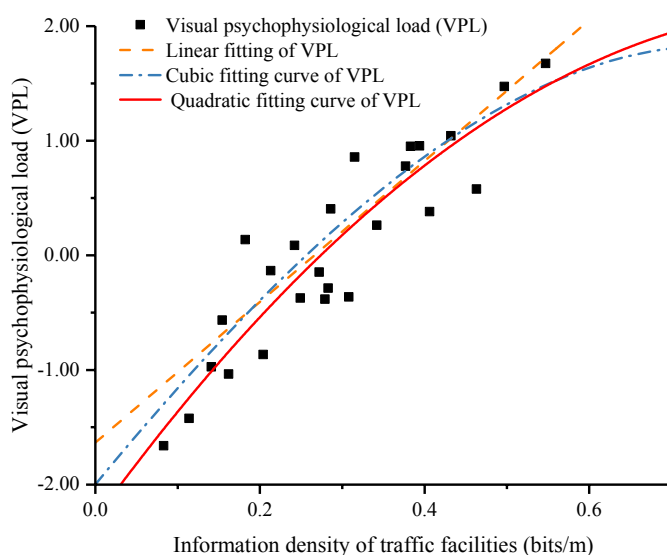
4.3 *Analysis of the correlation between the information density of traffic signs and driving comfort*

Scholars have now identified a degree of correspondence between driving visual comfort and driving load, but a variety of methods exist for quantitatively describing this relationship (Patoine et al., 2021; Shang et al., 2021; Zhang et al., 2021). Based on the existing research methods, this paper calculates the driver's eye movement load and heart rate load factor, and then establishes a formula to calculate the corresponding visual load value, and constructs a visual comfort regression model. According to this model, the correlation between traffic sign informativeness and visual comfort can be calculated, as shown in Table 11.

Table 11 Correlation between information density of traffic signs and visual comfort

		Information density (bits/m)	Eye movement load	Heartbeat load	Visual psychological load
Information density (bits/m)	Pearson correlation	1			
	Significance (bilateral)				
Eye movement load	Pearson correlation	0.836	1		
	Significance (bilateral)	0.000			
Heartbeat load	Pearson correlation	0.579	0.336	1	
	Significance (bilateral)	0.006	0.100		
Visual psychological load	Pearson correlation	0.891	0.931	0.622	1
	Significance (bilateral)	0.000	0.000	0.001	

In this paper, the relationship between drivers' visual mental load and traffic sign information density is fitted using linear regression, quadratic linear regression, and cubic linear regression analyses, respectively, to better quantitatively expose this relationship. Figure 5 illustrates the image results of all the three linear fits.

Figure 5 Fitting diagram of visual psychological load and information density of traffic signs (see online version for colours)

The results of the three kinds of line fits do not show much significant difference in the images, but it is easy to see that the three curves exhibit the same trend. In order to better judge which line fit is more appropriate, the fitting parameters of each regression model and the results of the F-test were compared.

According to the results presented in Table 12, the results of the F-test illustrate that all three models are effectively fitted. The R-squared value of the quadratic linear fit is the largest (0.754) among the three models, indicating that this linear fit has the most appropriate effect. Therefore, in this paper, we use the quadratic linear fitting function for quantitative analysis to establish a regression model, which demonstrates the relationship between the density of traffic sign information on urban roads and the visual mental load of drivers, as shown in equation (13):

$$S = -6.17x^2 + 11.11x - 2.52 \tag{13}$$

where S is the visual psychological load, x is the information density of the traffic signs.

Table 12 Fitting parameters and F-test results

Fitting equation form	The model parameters			F-test			
	R ²	R squared after adjustment	Standard error	d _{f1}	d _{f2}	F	Sig.
Linear	0.764	0.753	0.410	1	23	76.70	0.00
Quadratic	0.774	0.754	0.410	2	22	33.78	0.00
Cubic	0.778	0.746	0.416	3	21	24.53	0.00

As can be seen from Figure 5, the driver’s visual load, with the increase in the density of traffic sign information shows an increasing trend, indicating that there is a positive correlation with the density of traffic sign information. It can be verified that the driver’s comfort level is negatively correlated with the density of traffic sign information.

4.4 Analysis of traffic sign information density based on visual comfort

In a follow-up study, we found that for this experiment, the optimal range of traffic sign informativeness density was [0.021,0.725], which is a range in which drivers can have a proper sense of concentration without feeling uncomfortable. In a follow-up study, we found that for this experiment, the optimal range of information density of traffic sign is [0.021,0.725], which is a range in which drivers can have a proper sense of concentration without feeling uncomfortable. Equation (14) is used to perform visual load calculations, and when the information density of sign x_3 is outside of [0.021,0.725], it can be assumed that the driver is in an overly relaxed or tense state, and adjustments to the information density of sign are needed.

$$S = -6.17x^2 + 11.11x - 2.52 \tag{14}$$

Visual comfort directly affects the driver’s performance on the road (Monk et al., 2023). Table 13 shows the information density range criteria for grading different visual comfort levels. In order to keep the driver’s visual comfort always at an acceptable level, the information density of urban road traffic signs should be less than 0.373 bits per metre as far as possible, and in the case of a large number of road traffic signs, it should also be ensured that the maximum information density does not exceed 0.507 bits per metre, so as to guarantee that the driver’s visual load is at a level that is affordable to the driver.

Table 13 Range of information density of traffic sign on urban road for visual comfort

<i>Visual comfort level</i>	<i>S-threshold range of visual load</i>	<i>Information density of traffic signs</i>
Very comfortable	$-2.289 \leq S < -1.526$	$0 \leq x \leq 0.094$
More comfortable	$-1.526 \leq S < -0.763$	$0.094 \leq x \leq 0.175$
Comfortable	$-0.763 \leq S \leq 0.763$	$0.175 \leq x \leq 0.373$
Uncomfortable	$0.763 < S \leq 1.526$	$0.373 \leq x \leq 0.507$
Very uncomfortable	$1.526 < S \leq 2.289$	$0.507 \leq x$

5 Discussion

In terms of selecting experimental parameters, we selected test subjects with similar characteristics, with the aim of focusing on their physiological parameters and minimising the influence of other parameters on the results. However, we cannot ignore the factors such as the driver's gender, age, driving experience, time of day, weather, emotional state (Witt et al., 2019). We suggest that inappropriate road linear conditions may lead drivers to focus more on collecting information about road conditions and controlling the vehicle. Consequently, the time available for recognising signs information may be reduced, potentially affecting the relationship between the quantity of signs information and driver comfort.

This paper employs real vehicle tests to conduct a quantitative study on the optimal density of traffic sign on urban roads. Compared with the driving simulator experiments, the real vehicle experiments have a richer and more realistic and reliable data acquisition environment, which can better reproduce the conditions encountered in the actual driving process. However, real-vehicle experiments also have the challenges of higher costs, more restricted conditions, and more disturbing factors. However, the method is costly, requires specialised test equipment, and necessitates the recruitment of a group of test drivers – clear drawbacks of this research method. Future research could explore using driving simulators, provided that the driving scenarios are sufficiently varied. It is recommended to create video recordings of real driving scenes for use in driving simulators. Further studies should focus on the visibility of traffic sign on urban road sections with varying traffic volumes and under different weather conditions.

From the driver's perspective, the calculation of traffic sign information mainly involves colour and the text of the signs, and this calculation method has preliminarily incorporated these two important factors. But it also realises that this calculation method is somewhat simple, such as not taking into account the differences in information caused by the differences between different colours, and the differences in information content between different complex texts. Research in this area still needs to be fully integrated with information science.

In China, traffic laws and regulations vary from city to city in a way that is tailored to local characteristics, which may be culturally different or due to variations in objective conditions such as terrain and climate. Most of Nanchang is a plain terrain, with an overall subtropical monsoon climate, an average annual temperature of 17.7°C, an average annual rainfall of 1559.8 mm, with rainfall concentrated from April to June, and

wide, flat roads. Due to the flat terrain, the road is objectively representative of the vast majority of China's urban roads, and in terms of policy, although the laws are not exactly the same everywhere, none of the local laws are contrary to the 'Road Traffic Safety Law of the People's Republic of China'. There are only a few non-principled differences between local laws. The selected road sections are representative of most roads in China in terms of objective conditions and laws and regulations, and its driving environment, traffic management methods, and drivers' driving habits are all sufficiently representative. However, there may be some degree of difference in the detailed aspects such as the starting and ending time of the morning and evening peak hours, and the composition of the vehicle types of the traffic flow. Road traffic volumes and compositions should be explored to determine the extent to which these factors influence sign message content thresholds, given the different functions and road parameters of urban roads and expressways.

In the domain of traffic science, particularly from the vantage point of human factors, ascertaining the informational content of road traffic signs is pivotal for understanding the physiological responses of drivers under varying informational conditions, thereby facilitating their transition into a state of safe driving. Despite the rapid evolution and proliferation of intelligent driving and driver assistance systems in contemporary times, the decision-making process of the driver remains the paramount determinant of vehicular movement (Hu et al., 2024). The informational content of traffic signs serves as a critical tool in investigating the impact of signs with differing information densities on drivers, especially when augmented by driver assistance systems. It is essential to explore how these systems can prevent drivers from overlooking sign information, which could otherwise compromise safety. Furthermore, by examining the vehicle following pattern, one can discern how the interactive behaviour among multiple vehicles shifts in response to changes in sign information. This approach allows for a more macroscopic analysis of the traffic system's response to the cumulative effects of multiple signs along a road, providing insights into how sign information influences the overall traffic dynamics (Rahman et al., 2020).

6 Conclusion

In this paper, based on Shannon's information entropy theory, a method for calculating the information content of road traffic signs is proposed, a model for evaluating the driver's driving load through eye-movement load and heart-rate load is constructed, and the level of information density of road traffic signs is classified according to the driver's comfort level. The specific conclusions are obtained.

- 1 Significant associations were confirmed between eye movement loading parameters, heart rate parameters and driver driving comfort.
- 2 A model was established to calculate the visual psychological load of drivers by calculating eye movement and heart rate load.
- 3 Based on the degree of visual comfort, the information density of traffic signs was graded, and it was proposed that when setting up urban road traffic signs, the total amount of information contained in the sign elements should be less than 0.507 bits/m at the maximum.

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Conflict of interest

The authors declare no conflict of interest.

Ethics statement

The experiment has been approved by the Ethics Committee to ensure the rights and safety of the participants. All individuals participating in the experiment are doing so on the basis of informed consent and have the right to withdraw at any time. Personal privacy information will be strictly protected during the experiment to ensure the confidentiality and security of the data, which will only be used for research purposes. At the same time, we will make every effort to minimise physical and mental harm to individuals during the experiment, ensuring that the experiment complies with ethical and safety standards. All participants provided written informed consent to participate in the study. The participant in Figure 1 has provided a written informed consent form to publish the figure.

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