# Graded Responses and Evaluation of Driving Characteristics under Road Hazard Stress

**Authors:** Zheng Xinyi, YANG Yanqun, Chen Ming, Said Easa, Zheng Xinyi

**Date:** 2022-03-15T09:46:33Z

## Abstract

[Objective] To investigate whether driving characteristics influence drivers' stress responses and behaviors when facing traffic hazard events. [Methods] This study employed the Vienna Traffic Psychological Test System (VTS) to test participants in a driving simulation experiment. In the driving simulation experiment, participants were required to drive at a speed of 60 km/h, with three distance settings between the stressor and the participant' s vehicle corresponding to Time-to-Collision (TTC): 19.2 m (TTC=1 s), 27.5 m (TTC=1.5 s), and 35.8 m (TTC=2 s). The study utilized a set pair analysis model to evaluate the quality of participants' stress responses, where the range of evaluation grades for indicators was determined by K-means clustering, and the weights of indicators were determined by the entropy weight method. [Results] The results demonstrate that judging drivers' stress response capabilities through driving characteristics is effective, manifesting in two specific aspects: First, under all stress distances, participants with high driving characteristics exhibited superior stress responses compared to those with low driving characteristics; Second, when the stress distance was 19.2 m (TTC=1 s), the response evaluation for participants with high driving characteristics was two grades higher than that for participants with low driving characteristics, whereas at other stress distances it was only one grade higher, indicating that participants with low driving characteristics were more sensitive to reductions in stress response distance than those with high driving characteristics. [Limitations] Insufficient demographic representation in the sample. [Conclusion] The findings of this study substantiate the rationality of providing drivers with more than 1 s of Time-to-Collision in traffic stress events, which can offer references for the design of accident warning and collision avoidance systems. Additionally, the mathematical method for grade evaluation proposed in this study is effective; by detecting drivers' driving characteristic capabilities, their stress response capabilities on the road can be distinguished. This study provides a feasible rating approach for research in the field of road traffic safety.

## Full Text

# Road Risk Response and Rank Assessment Based on Driver Characteristics

**Zheng Xinyi[1,3]***, Yang Yanqun[2,3], Chen Ming[2], Easa Said[3],
[1] College of Arts and Humanities, Fuzhou University
[2] College of Civil Engineering, Fuzhou University
[3] Center for Transportation Safety, Fuzhou University, Fuzhou 350109, China
College of Civil Engineering, Ryerson University, Canada

[**Objective**] To explore whether driving characteristics affect drivers' stress responses and behaviors when facing traffic hazard events.
[**Methods**] This study employed the Vienna Test System (VTS) to assess participants in a driving simulation experiment. In the simulation, participants were required to drive at 60 km/h while encountering stressors at three distances corresponding to Time-to-Collision (TTC) values: 19.2 m (TTC = 1 s), 27.5 m (TTC = 1.5 s), and 35.8 m (TTC = 2 s). A set pair analysis model evaluated participants' stress responses, with evaluation grade ranges determined by K-means clustering and indicator weights assigned via the entropy weight method.
[**Results**] The findings demonstrate that assessing drivers' stress response capabilities through driving characteristics is effective. First, across all stress distances, participants with high driving characteristics exhibited superior stress responses compared to those with low driving characteristics. Second, at a stress distance of 19.2 m (TTC = 1 s), the evaluation score for high-characteristic participants was two levels higher than for low-characteristic participants, whereas at other distances the difference was only one level. Low-characteristic participants showed greater sensitivity to reductions in stress distance than their high-characteristic counterparts.
[**Limitations**] The demographic composition of the study sample was insufficiently diverse.
[**Conclusions**] This study validates the rationale for providing drivers with more than 1 s of TTC in traffic stress events, offering reference values for accident warning and collision avoidance system design. The proposed mathematical grading method proves effective, enabling differentiation of drivers' on-road stress response capabilities through assessment of their driving characteristics. This research provides a feasible rating framework for road traffic safety studies.

**Keywords:** Driving characteristics, Stress response, Set Pair Analysis, Driving simulation
**Classification:** U491.2

---

## Abstract

[**Objective**] To investigate whether driving characteristics influence drivers' stress responses and behaviors during traffic hazard events.

This work was supported by the Fujian Provincial Social Science Fund (Project No. 2021B63).
*Corresponding author: Zheng Xinyi, E-mail: zhengxinyi@fzu.edu.cn*

[**Methods**] The Vienna Test System (VTS) was used to evaluate participants in a driving simulation experiment. Participants drove at 60 km/h while the distance between the stressor and their vehicle corresponded to three Time-to-Collision (TTC) scenarios: 19.2 m (TTC = 1 s), 27.5 m (TTC = 1.5 s), and 35.8 m (TTC = 2 s). Set pair analysis evaluated stress responses, with K-means clustering determining evaluation grade ranges and the entropy weight method establishing indicator weights.

[**Results**] Results confirm that judging drivers'stress response ability via driving characteristics is effective. First, under all stress distances, high-characteristic participants outperformed low-characteristic participants. Second, at 19.2 m (TTC = 1 s), high-characteristic participants scored two levels higher than low-characteristic participants, while at other distances the advantage was only one level. Low-characteristic participants demonstrated heightened sensitivity to reduced stress distances.

[**Limitations**] The sample lacked sufficient demographic diversity among driver characteristics.

[**Conclusions**] This study substantiates the necessity of providing drivers with TTC exceeding 1 s during traffic stress events, informing the design of warning and anti-collision systems. The proposed grading methodology effectively distinguishes drivers' stress response capabilities through characteristic assessment, offering a viable rating approach for road safety research.

**Keywords:** Driver characteristics, Stress response, Set Pair Analysis, Driving Simulation Experiment

---

## 1 Introduction

Due to the complexity of traffic environments, drivers often fail to avoid traffic stress events in time (e.g., pedestrians suddenly darting from the roadside, vehicles emerging from sight-restricted intersections), leading to accidents through erroneous operations. Analysis of accident mechanisms reveals that differences in stress response capabilities stemming from driver characteristics constitute a critical factor affecting crash occurrence. Accident proneness theory suggests that certain individuals differ in physiological and psychological capacities related to safety personality traits [1,2], while research indicates that drivers'stress responses decline as the urgency of road stress events increases [3,4]. We posit that variations in drivers' physiological and psychological abilities manifest differently across driving behaviors as road environmental stress intensifies.

Scholars worldwide have investigated stress response capabilities across drivers with different characteristics. For instance, individuals with lower attention levels exhibit longer perception-reaction times (from lead vehicle brake light illumination to driver' s foot leaving the accelerator) and brake-movement times (from foot leaving accelerator to contacting brake) when facing stress events [5]. Novice and experienced drivers show differences in average speed and maximum brake depth under various stress conditions [6]. Warshawsky-Livne et al. found that perception-reaction time increased significantly with age and event urgency across three stress scenarios [3]. Takahashi et al. assessed drivers' hazard perception by measuring palm sweat response (PSR), skin potential reflex (SPR), and steering wheel, accelerator, and brake operation abilities in elderly drivers [7]. Domestic research has focused on identifying indicators characterizing stress response capacity, such as the relationship between training frequency and pupil area change rate in complex road environments [8], and significant differences in heart rate growth rates across various conflict-induced stress scenarios [9]. However, studies on stress responses among different driver characteristics remain relatively scarce domestically.

Nevertheless, definitions and research foci regarding driving characteristics vary internationally. To clarify the content of driving characteristics, this paper adopts the S-O-R (Stimulus-Organism-Response) model from cognitive psychology to divide driver behavior into three stages: information perception, judgment/decision-making, and driving operation [10]. The perception stage primarily receives external information; the judgment stage involves analysis-based decision-making; and the operation stage represents actual responses, specifically steering, braking, and acceleration controls. Accordingly, driving characteristics are categorized into perceptual, judgmental, and operational characteristics.

Research on drivers' perceptual characteristics has long established that among accidents caused by driver error, perceptual errors account for 50.2%, judgment/decision errors for 38.9%, and operational errors for 10.9% [11]. Tuerker et al., through questionnaires on driver accident rates in Sweden and Turkey, found that drivers in low-accident countries perceived speed more accurately than those in high-accident countries [12]. Novice drivers' hazard perception correlates with their accident records [13], and hazard perception ability improves with increased negative emotions [14]. Elderly drivers' capacity to continuously receive and process spatiotemporal information from the environment declines, exposing operational risks (braking, steering, starting, merging, lane-changing) during emergencies [15]. Regarding judgment characteristics, Wu Fuwei tested accident-involved and accident-free drivers using a complex reaction test system, finding no significant differences in judgment criteria but weaker complex information processing and executive functions in the accident group [16]. For operational characteristics, Summala found that time from stressor appearance to initial brake pedal contact depended heavily on the traffic scenario [17], and drivers braked more readily when pedestrians appeared on the right versus left side [18]. In summary, driving characteristics—particularly perceptual characteristics—significantly impact traffic safety across varying stress scenarios.

Regarding measurement tools, studies have employed questionnaires [14,19] or testing instruments [16,20–24] to determine driving characteristics, such as risk perception scales, emotion tests [14], and driving risk attitude scales [19]. Some research developed custom equipment to test drivers' complex reactions [16]. Notably, the Vienna Test System (VTS) has proven superior for assessing driver characteristics. KAÇA G compared three mandatory psychological assessment systems for professional and license-suspended drivers in Turkey—VTS, ART 2020, and TRAFIKENT—finding VTS' s six test modules significantly correlated with driving error (violation) counts, with the Concentration Test (COG) showing predictive value for violations [20]. Deng used VTS Peripheral Perception (PP) and Visual Reaction (VR) modules to explore gender and experience differences, revealing no gender differences in PP but experienced drivers outperforming novices [21]. Soheil et al. employed COG, Adaptive Traffic Perception (ATAVT), Reaction Time (RT), and Reactive Stress Tolerance (DT) modules to measure driving characteristic changes in waterpipe smokers before and after consumption [22]. Hani Tabai et al. used Sustained Attention (WAFV), Visual Perception (LVT), and COG tests to evaluate cognitive differences between train drivers with and without accident histories [23]. Mihai et al. utilized Safety Assessment Road and Driver Personality Factors Road test groups to assess psychophysical abilities and personality traits required for safe driving [24].

Despite extensive international use of VTS for measuring driving characteristics, comparative evaluations under specific road stress scenarios remain limited, particularly in domestic research. Therefore, this study employs VTS to detect participants' driving characteristic levels, selects groups with distinct differences, collects stress response data across varying stress scenarios via driving simulation, and establishes a mathematical analysis method to evaluate driver performance based on stress response quality (safety level).

---

## 2.1 Participant Recruitment

This experiment recruited 100 licensed drivers for VTS testing. Participants with one or more years of driving experience comprised 64% of the sample, aged 20–26 years, including 70 males and 30 females, aligning with 2018 Chinese driver demographic statistics [25]. Based on existing driving simulation research [22,23,26], 42 participants were selected for the driving simulation experiment.

---

## 2.2 VTS Test Design

### (1) VTS Module Selection

As previously established, driver behavior comprises three interrelated and continuous stages—perception, judgment, and operation—that cannot be simply separated. Therefore, VTS modules relevant to these three stages were selected to assess driving characteristics. Based on the VTS manual and domestic/international research applications [22-24,27], five test modules were chosen (Table 1).

**Table 1 Driving Characteristic Test Items Battery**

| Module Content | Test Name | Assessment Focus |
|---|---|---|
| Logical reasoning ability | Adaptive Matrices Test (AMT) | Assesses logical reasoning, attention concentration, and comprehensive judgment [24] |
| Traffic perception ability | Adaptive Traffic Perception Test (ATAVT) | Briefly presents traffic images requiring responses; evaluates visual observation, spatial perception, and speed perception [22,24,28] |
| Concentration test | COG | Determines whether displayed numbers match any of four previously shown numbers; tests attention level [20,22-24] |
| Reaction ability test | RT | Requires immediate button press upon key stimulus appearance; tests reaction capability [22,24] |
| Reactive stress tolerance | DT | Press corresponding buttons in response to continuous visual and auditory stimuli at three speeds; tests eye-ear-hand-foot coordination [20,22,24] |

The PR value (percentile rank) quantifies VTS results [22,24,27], representing the proportion of individuals in the reference group (a representative European sample) who scored at or below the same level. The sum of PR values across five modules yields the driver' s characteristic score, with higher scores indicating better driving characteristics.

## 2.3 Driving Simulation Experiment Design

### (1) Experimental Scenario Design

The stress event involved a parked vehicle (stressor) suddenly emerging from an obscured area ahead of the participant’ s vehicle, traveling at low speed in the same lane before changing lanes and stopping. Figure 1 illustrates the experimental scenario containing the stressor.

Driver characteristics (internal factor) and stress distance (external factor) both influence stress responses. Research indicates that stress distance variations affect heart rate growth and LF values of heart rate variability more substantially than speed changes [4]. Therefore, this study controlled speed at 60 km/h while investigating responses across different stress distances. Accounting for the participant vehicle’ s front length, distances corresponding to TTC values of 1.0 s, 1.5 s, and 2.0 s were set at 19.2 m, 27.5 m, and 35.8 m, respectively [4].

To prevent psychological expectancy, six potential stress event trigger points were designed, but only the 2nd, 5th, and 6th locations actually triggered events. To counteract learning effects across three stress events, three scenarios with different trigger distance sequences were created: Scenario A (19.2 m, 27.5 m, 35.8 m), Scenario B (27.5 m, 35.8 m, 19.2 m), and Scenario C (35.8 m, 19.2 m, 27.5 m). These scenarios were rotated among participants.

### (2) Stress Response Indicators

When encountering stressors, drivers respond laterally via steering and longitudinally via accelerator release or braking. Based on relevant literature [29-32], accelerator depth, brake speed, and steering wheel angle were selected to characterize driving behavior. EEG and eye movement indicators representing physiological/psychological status are listed in Table 2.

**Table 2 Stress Response Indices**

| Indicator Type | Indicator | Description |
|---|---|---|
| EEG | ( + )/ | Calculated from , , and wave energies; indicates alertness (lower values = lower alertness) [33-35] |
| Eye movement | Saccade frequency | Ratio of target observations to time; indicates environmental familiarity (lower frequency = greater familiarity, less psychological pressure) [30] |

| Indicator Type | Indicator | Description |
|---|---|---|
| Eye movement | Pupil area (pixel) | Reflects visual adaptability and physiological/psychological load; larger pupil area indicates higher task load [32] |
| Driving behavior | Accelerator depth (cm) | Accelerator pedal depth; greater depth indicates tendency to maintain or increase speed |
| Driving behavior | Brake speed (cm/s) | Brake depth divided by braking time; higher values indicate more urgent braking and more intense stressor reaction |
| Driving behavior | Steering wheel angle (°) | Angle change per steering adjustment; larger values indicate more intense stress responses |

### (3) Experimental Equipment

The experiment was conducted indoors to eliminate weather, lighting, and noise influences on physiological responses.

1. **Driving simulation system**: The DSR-1000TS2.0 system enabled closed-loop indoor simulation, recording multiple driving behavior parameters (steering angle, brake/accelerator depth) and vehicle parameters (speed, acceleration, trajectory deviation).
2. **EEG data acquisition**: A 32-channel NE wireless EEG system transmitted 24-bit data with 0–250 Hz bandwidth, 500 SPS sampling rate, 24-bit/0.05 V resolution, and <1 Vrms noise (0–250 Hz).
3. **Eye movement data acquisition**: A Dikablis eye tracker with D-Lab analysis software tracked and measured eye movement characteristics at 60 Hz frequency with 0.1°–0.3° precision.

---

## 2.4 Experimental Procedure

All 100 recruited participants first completed VTS testing. Based on results, 21 high-characteristic and 21 low-characteristic participants were selected for driving simulation.

**VTS Testing**: Participants completed personal information forms (age, driving experience, annual mileage) and received VTS usage instructions. Testing duration was approximately 30 minutes.

**Driving Simulation**: Before formal experiments, participants were informed of objectives and tasks, emphasizing the 60 km/h speed requirement, and signed consent forms. Researchers fitted participants with EEG and eye-tracking equipment. Participants practiced 5–10 minutes in non-experimental scenarios to familiarize themselves with the simulator.

Formal experiments involved loading one scenario (A, B, or C) with approximately 10 minutes of driving per participant, with each participant driving only once.

---

## 2.5 Data Processing

VTS data (PR values) were directly exported. Eye movement data were exported via D-Lab. Driving data were automatically generated at 30 ms intervals. EEG data were processed using NIC software and EEG-Lab in MATLAB, filtering 0.5–40 Hz data (at 500 Hz sampling), re-referencing to the mean, and performing ICA to remove artifacts.

Two male participants with abnormally low PR values (<3) were excluded. From the remaining 98 participants, the 21 highest-scoring individuals (18 males, 3 females) formed the high-characteristic group (Group H), while the 21 lowest-scoring (14 males, 7 females) formed the low-characteristic group (Group L).

Independent samples t-tests on the six driving characteristic indicators revealed significant differences between groups (Table 3). Levene' s test for equality of variances could not reject the null hypothesis of equal variances for any indicator.

**Table 3 Independent-Samples T Test of Driving Characteristic Indicators**

| Driving Characteristic Indicator | Mean Difference | 95% CI (Lower) | 95% CI (Upper) | p-value |
|---|---|---|---|---|
| Logical reasoning (AMT) | 21.857 | 0.017** | | |
| Concentration (COG) | 13.381 | 0.012** | | |
| Traffic perception (ATAVT) | 16.905 | 0.015** | | |

| Driving Characteristic Indicator | Mean Difference | 95% CI (Lower) | 95% CI (Upper) | p-value |
|---|---|---|---|---|
| Reaction speed (RT) | | 0.000** | | |
| Movement speed (RT) | | 0.001** | | |
| Reactive stress tolerance (DT) | | 0.000** | | |

*Note:* p<0.1 (marginally significant), ** p<0.05 (significant), *** p<0.01 (highly significant).*

---

## 3.2 Driving Simulation Experiment Results

Two-way repeated measures ANOVA (with three stress distances as the repeated factor) was performed on each stress response indicator (Table 4). Mauchly' s sphericity test indicated that only "pupil area" met the sphericity assumption; Greenhouse-Geisser corrections were applied to other indicators.

**Table 4 Two-Way Repeated Measures Analysis of Stress Response Indicators**

| Indicator | Stress Distance | Driving Characteristic | Distance × Characteristic |
|---|---|---|---|
| ( + )/ Saccade frequency | 0.018* | 0.009* | 0.001* |
| Pupil area | 1.776 | | |
| Accelerator depth | | | |
| Brake speed | | | |
| Steering angle | | | |

*Note: b indicates the statistic is an upper bound on F, yielding a lower bound on significance level.*

Results showed significant within-subject effects of stress distance for all indicators (p<0.01). The interaction between stress distance and driving characteristics significantly affected brake speed. Between-subject effects of driving characteristics were significant for all indicators (p<0.01).

Regarding effect sizes, Ferguson' s [36] benchmarks for small, medium, and large effects in social sciences are 0.04, 0.25, and 0.64, respectively. Table 4 shows that for stress distance, the variance explained exceeded 0.64 for accelerator depth, brake speed, steering angle, and pupil area, while ( + )/ and saccade frequency fell between 0.25-0.64, indicating substantial practical significance. For driving characteristic groups, pupil area, accelerator depth, brake speed, and ( + )/ explained 0.25-0.64 of variance, while steering angle and saccade frequency explained 0.04-0.25, demonstrating varying degrees of practical significance.

Overall, Group H outperformed Group L across all indicators. Longer stress distances yielded safer and more stable physiological, psychological, and behavioral responses. Specific analyses follow:

**1) EEG Indicator**: Group L showed higher ( + )/ values than Group H, indicating higher alertness during stress. Smaller stress distances produced larger ( + )/ values, reflecting increased alertness under more urgent conditions.

**2) Eye Movement Indicators**: Group L exhibited higher saccade frequency than Group H, indicating greater psychological pressure. Saccade frequency increased at shorter distances, reflecting heightened mental stress. Similarly, Group L' s pupil area exceeded Group H' s, indicating greater mental load, with pupil area increasing as stress distance decreased.

**3) Driving Behavior Indicators**: Group H demonstrated greater accelerator depth than Group L, with depth increasing at longer distances, suggesting that better driving characteristics or longer reaction time/space enhance accelerator control and permit higher speeds. Group L showed higher brake speed than Group H, indicating more urgent braking that intensified at shorter distances. The significant interaction between characteristics and distance on brake speed suggests these factors jointly influence braking behavior. For steering angle, Group L exceeded Group H, showing more intense stress responses that amplified at shorter distances.

---

## 4 Stress Response Evaluation Based on Set Pair Analysis

To comprehensively represent stress responses of high- and low-characteristic groups across different distances, this study introduced set pair analysis. Building on six indicators, K-means clustering determined evaluation grade ranges while entropy weighting established indicator weights.

### 4.1 K-Means Clustering for Evaluation Grade Ranges

Evaluation criteria must be established before assessment. As a representative unsupervised clustering algorithm, K-means automatically groups similar samples [37]. This study used SPSS to cluster samples into five categories, determining five-grade ranges for six indicators based on cluster centers.

Cluster centers for each indicator were standardized and distributed as shown in Figure 3. Saccade frequency, pupil area, and brake speed showed ordinal relationships with categories. Accelerator depth showed an inverse ordinal relationship. Although category 4 cluster centers for ( + )/ and steering angle exceeded category 5, they generally followed ordinal patterns.

**Figure 3** Standardized cluster center values for indicators

Categories 1–5 corresponded to stress levels from highest to lowest. Table 5 presents the resulting grade ranges, where Grade 1 represents the highest evaluation level and Grade 5 the lowest.

**Table 5 Indicators' Range of Five Levels**

| Indicator | Grade 1 | Grade 2 | Grade 3 | Grade 4 | Grade 5 |
|---|---|---|---|---|---|
| ( + )/ | 0.54–2.19 | 2.20–2.98 | 2.99–4.10 | 4.11–5.14 | 5.15–11.52 |
| Saccade frequency | 0.10–0.21 | 0.22–0.27 | 0.27–0.34 | 0.35–0.43 | 0.44–1.06 |
| Pupil area | 878.65–1009 | 1009.63–1201.5 | 1201.53–1396.92 | 1396.92–1573.16 | 1573.16–1683. |
| Accelerator depth | 1.97–3.24 | 1.52–1.96 | 0.96–1.51 | 0.64–0.95 | 0.13–0.63 |
| Brake speed | 0.56–1.10 | 1.11–1.71 | 1.72–2.65 | 2.66–3.23 | 3.24–7.36 |
| Steering angle | 0.81–1.44 | 1.45–1.73 | 1.74–2.08 | 2.09–7.84 | |

### 4.2 Entropy Weight Method for Indicator Weights [38,39]

The entropy weight method is an objective weighting approach that determines weights based on information content. The procedure is as follows:

**1) Indicator normalization**: Due to differing dimensions and magnitudes among EEG, eye movement, and driving indicators, data were standardized using formulas (1) and (2) for benefit-type and cost-type indicators, respectively.

$$v_{ij} = \frac{u_{ij} - \min(u_j)}{\max(u_j) - \min(u_j)} \quad (1)$$

$$v_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (2)$$

where $u_{ij}$ is the value of indicator $j$ for sample $i$, $v_{ij}$ is the standardized value, $\max(u_j)$ is the maximum value, and $\min(u_j)$ is the minimum value.

**2) Calculate characteristic proportion** $p_{ij}$ for sample $i$:

$$p_{ij} = \frac{v_{ij}}{\sum_{i=1}^{m} v_{ij}} \quad (3)$$

**3) Calculate information entropy** $e_j$ for indicator $j$:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij}\ln(p_{ij}) \quad (4)$$

**4) Calculate entropy weight** $w_j$:

The greater the variation in indicator $j$ across evaluated objects, the more information it conveys. When all values for indicator $j$ are equal, $e_j = 1$. The difference coefficient $d_j = 1 - e_j$ is defined, where larger $d_j$ indicates greater information provision and higher weight. The entropy weight is:

$$w_j = \frac{d_j}{\sum_{k=1}^{m} d_k} \quad (5)$$

Resulting weights are shown in Table 6.

**Table 6 Indicator Weight Obtained by Entropy Method**

| Indicator | Weight |
|---|---|
| ( + )/ | |
| Saccade frequency | |
| Pupil area | |
| Accelerator depth | |
| Brake speed | |
| Steering angle | |

### 4.3 Set Pair Analysis Evaluation Model

Set pair analysis (SPA) treats deterministic and uncertain relationships between studied objects as a deterministic-uncertain system. SPA has been widely applied in computer science [40], biochemistry [41], transportation [42,43], materials science [44], engineering [45], physics/astronomy [46], and environmental science [47].

SPA evaluation forms a pair $(A, B)$ from two interrelated sets. If both sets belong to the same evaluation grade, they exhibit identity; if grades are separated, they show opposition; if adjacent, they show difference. Analyzing identity, difference, and opposition establishes the connection degree:

$$\mu = \frac{S}{N} + \frac{F}{N}i + \frac{P}{N}j = a + bi + cj \quad (6)$$

where $\mu$ is the connection degree, $N$ is the total feature count, $S$ is identical features, $F$ is differential features, and $P$ is opposite features. $i$ is the difference coefficient, $j$ is the opposition coefficient, $a$ is identity degree, $b$ is difference degree, and $c$ is opposition degree, with $a + b + c = 1$.

Further subdividing difference and opposition degrees yields a five-element connection degree (7). For the evaluated object indicator set $A = [x_1, x_2, ..., x_6]$ and five-grade standard set $B = [s_0 \sim s_1, s_1 \sim s_2, ..., s_4 \sim s_5]$, for cost-type indicators, when $x_j$ falls within grade range $s_{k-1} \sim s_k$, $a = 1$. When $x_j$ falls in adjacent grades, if $x_j < s_{k-1}$ it is considered superior difference (denoted $b_1$); if $x_j > s_k$ it is inferior difference ($b_2$). When $x_j$ falls in separated grades, if $x_j < s_{k-2}$ it is superior opposition ($c_1$); if $x_j > s_{k+1}$ it is inferior opposition ($c_2$).

Thus, equation (6) becomes [47]:

$$\mu = a + b_1 i + b_2 i + c_1 j + c_2 j \quad (7)$$

For cost-type indicators, the connection degree vector $\mu_j(k)$ for sample $i$' s indicator $j$ at grade $k$ is calculated using expression (8). For benefit-type indicators (accelerator depth), the domain endpoints in (8) are reversed.

The comprehensive connection degree vector $\mu$ is calculated by combining indicator weights with grade-specific connection degrees using formula (9). SPA defines the set pair potential as the ratio of identity to opposition degree, extended to generalized set pair potential [48] in equation (10).

Evaluation grades are typically determined by the maximum set pair potential principle (11). Final set pair potentials for both groups across three distances appear in Table 7.

**Table 7 Set Pair Analysis Evaluation Results**

| Stress Distance | High Characteristic | Low Characteristic |
|---|---|---|
| 19.2 m | 1.504 (Grade 2) | |
| 27.5 m | | |
| 35.8 m | | |

Results show that high-characteristic participants outperformed low-characteristic participants across all distances, confirming that driving characteristics can predict stress response capability. When distance decreased from 27.5 m to 19.2 m, high-characteristic participants dropped from Grade 2 to Grade 3, while low-characteristic participants fell from Grade 3 to Grade 5, demonstrating greater sensitivity to distance reduction among low-characteristic drivers. When distance decreased from 35.8 m to 27.5 m, both groups dropped one grade, consistent with research showing no significant psychological load difference between 35.8 m (TTC=2s) and 27.5 m (TTC=1.5s), but significant differences between 27.5 m and 19.2 m (TTC=1s) [4]. This highlights the critical importance of TTC exceeding 1 s.

Individual sample assessments were calculated for 216 samples (2 groups × 3 distances). Figure 4 illustrates the distribution: for low-characteristic participants at 19.2 m, 6 were rated Grade 3, 7 Grade 4, and 8 Grade 5 (with 8/17 of all Grade 5 ratings belonging to this subgroup). Grade 3 was most common across conditions, indicating intermediate stress response levels. Grade 1 primarily came from high-characteristic participants at 27.5 m and 35.8 m, with a few from low-characteristic participants at 35.8 m, suggesting some low-characteristic individuals performed excellently with sufficient distance. However, most low-characteristic participants at 35.8 m received Grade 3, with Grade 1 counts matching Grades 4 and 5, indicating instability even at longer distances. High-characteristic participants showed stable performance (Grades 1-3) at 27.5 m and 35.8 m, with only Grade 3-5 ratings at 19.2 m. Both groups exhibited evenly distributed ratings (Grades 3-5) at 19.2 m, indicating poor stress responses at TTC = 1 s.

**Figure 4** Set pair analysis grade distribution for two driving characteristic groups across three stress distances

---

## 5 Conclusion and Discussion

1. VTS testing successfully screened 21 high-characteristic and 21 low-characteristic participants, with independent samples t-tests confirming significant differences across all indicators.

2. Six indicators—EEG ( + )/ , pupil area, saccade frequency, accelerator depth, brake speed, and steering angle—were analyzed across three stress distances. Significant differences emerged between groups and across distances, with high-characteristic participants outperforming low-characteristic participants and longer distances producing superior values. These results validate the hypotheses proposed in the introduction.

3. Set pair analysis revealed that high-characteristic participants outperformed low-characteristic participants at all distances, with performance improving at longer distances. Notably, low-characteristic participants at 35.8 m outperformed high-characteristic participants at 19.2 m. The two-grade advantage for high-characteristic participants at 19.2 m versus one-grade advantages at other distances underscores low-characteristic participants' heightened sensitivity to distance reduction, emphasizing the need for characteristic improvement.

4. The significant interaction between characteristics and distance on brake speed suggests distance reduction impacts low-characteristic participants more severely. Better characteristics or longer reaction time/space corre-

late with higher speeds (greater accelerator depth), likely due to superior accelerator control.

5. The one-grade decline for both groups when distance decreased from 35.8 m to 27.5 m aligns with findings of no significant psychological load difference between these distances but significant differences between 27.5 m and 19.2 m [4]. This confirms TTC > 1 s as a critical threshold for safe stress responses.

6. The maximum set pair potential principle, similar to fuzzy evaluation' s maximum membership principle, overemphasizes extreme values while losing intermediate information. For instance, a sample with potentials [1.1, 2.1, 1.4, 2.0, 2.2] would be rated Grade 5 despite Grades 3–5 being similar. Alternative confidence criteria require membership >0.5, which would prevent Grade 1 ratings (e.g., sample [0.45, 0.7, 0.16, 0.16, 0.16] would be Grade 2, not Grade 1). Future research should develop a method combining maximum potential with confidence criteria.

7. This study established the relationship between VTS-assessed driving characteristics and stress responses but did not investigate methods for improving characteristics through VTS training—a crucial direction for future research.

**Author Contributions**: Zheng Xinyi conceptualized the study, designed the framework, and revised the manuscript. Yang Yanqun proposed methods, conducted experiments, and provided data. Chen Ming collected and analyzed data and drafted the manuscript. Easa Said conceptualized the study and finalized the manuscript.

**References** [1] AL-MADANI H, AL-JANAHI A R. Role of Drivers' Personal Characteristics in Understanding Traffic Sign Symbols[J]. Accident Analysis & Prevention, 2002, 34(2): 185-196. [2] NORRIS F H, MATTHEWS B A, RIAD J K. Characterological, Situational, and Behavioral Risk Factors for Motor Vehicle Accidents: A Prospective Examination[J]. Accident Analysis & Prevention, 2000, 32(4): 505-515. [3] WARSHAWSKY-LIVNE L, SHINAR D. Effects of Uncertainty, Transmission Type, Driver Age and Gender on Brake Reaction and Movement Time[J]. Journal of Safety Research, 2002, 33(1): 117-128. [4] 王畅, 鲁玉萍, 付锐, et al. 行人突然侵入道路时驾驶人的生理负荷特性研究[J]. 科学技术与工程, 2016, 1(21): 106-111. (WANG Chang, LU Yu-ping, FU Rui, et al. Parameters Analysis of Physiology Load of Drivers During Stress Response[J]. Science Technology and Engineering, 2016, 1(21): 106-111.) [5] ZHANG L, BALDWIN K, MUNOZ B, et al. Visual and Cognitive Predictors of Performance on Brake Reaction Test: Salisbury Eye Evaluation Driving Study[J]. Ophthalmic Epidemiology, 2007, 14(4): 216-222. [6] WANG Y, LIAO K-B, ZHANG W, et al. Application of Driving Simulation System on Testing Driver' s Reaction to Road Hazards[J]. 2011, 23: 1251-1255+1277. [7] TAKAHASHI R, KOBAYASHI M, SASAKI T, et al. Driving Simulation Test for Evaluating Hazard Perception: Elderly Driver Response Characteristics[J].

Transportation Research Part F: Traffic Psychology and Behaviour, 2017, 49: 257-270. [8] 赵亮, 刘浩学, 石保同. 复杂道路环境中驾驶人应激反应能力研究 [J]. 中国安全科学学报, 2015, 25(4): 105-109. (ZHAO Liang, LIU Hao-xue, SHI Bao-tong. Stress Response Ability of Drivers in Complex Road Environment[J]. China Safety Science Journal, 2015, 25(4): 105-109.) [9] 李显生, 孟凡淞, 郑雪莲, et al. 基于心率变异性的应激场景下驾驶人心理特性分析 [J]. 上海交通大学学报, 2018(2): 163-168. (LI Xian-sheng, MENG Fan-song, ZHENG Xue-lian, et al. Psychological Characteristics of Drivers in the Stress Scene Based on Heart Rate Variability[J]. Journal of Shanghai Jiaotong University, 2018(2): 163-168.) [10] WETTON M A, HORSWILL M S, HATHERLY C, et al. The Development and Validation of Two Complementary Measures of Drivers' Hazard Perception Ability[J]. Accident Analysis & Prevention, 2010, 42(4): 1232-1241. [11] MA Y, LOU Y, WANG Y. Road Traffic Accidents Model and Its Application Based on Driver' s Self-Mistakes[J]. Journal of Transportation Systems Engineering and Information Technology, 2010, 10(4): 101-105. [12] TUERKER Oe, LAJUNEN T, WARNER H W. Cross-Cultural Differences in Drivers' Speed Choice[J]. Accident Analysis & Prevention, 2009, 41(4): 816-819. [13] DEERY H A. Hazard and Risk Perception among Young Novice Drivers[J]. Journal of Safety Research, 1999, 30(4): 225-236. [14] HU T Y, XIE X, LI J. Negative or Positive? The Effect of Emotion and Mood on Risky Driving[J]. Transportation Research Part F: Traffic Psychology and Behaviour, 2013, 16: 29-40. [15] RANNEY T A. Models of Driving Behavior: A Review of Their Evolution[J]. Accident Analysis & Prevention, 1994, 26(6): 733-750. [16] 吴付威. 基于信息处理机制的驾驶人感知-判断-反应特性研究 [D]. 长安大学, 2020. (WU Fu-wei. Research on Drivers' Perception-Judgement-Response Characteristics Based on Information Processing[D]. Chang' an University, 2020.) [17] SUMMALA H. Brake Reaction Times and Driver Behavior Analysis[J]. Transportation Human Factors, 2000, 2(3): 217-226. [18] JURECKI R S, STANCZYK T L. Driver Reaction Time to Lateral Entering Pedestrian in a Simulated Crash Traffic Situation[J]. Transportation Research Part F: Psychology and Behaviour, 2014, 27(Part A): 22-36. [19] ULLEBERG P, RUNDMO T. Risk-Taking Attitudes among Young Drivers: The Psychometric Qualities and Dimensionality of an Instrument to Measure Young Drivers' Risk-Taking Attitudes[J]. Scandinavian Journal of Psychology, 2010, 43(3): 227-237. [20] KAÇA G, İZMITLIGIL T, KOYUNCU M, et al. How Well Do the Traffic Psychological Assessment Systems Predict On-Road Driving Behaviour?[J]. Applied Cognitive Psychology, 2021, 35(5): 1321-1337. [21] DENG M, WU F, GU X, et al. A Comparison of Visual Ability and Its Importance Awareness between Novice and Experienced Drivers[J]. International Journal of Industrial Ergonomics, 2021, 83(April): 103141. [22] SAADAT S, SABAGH M S, KARBAKHSH M. The Effect of Waterpipe Smoking on Psychomotor Performance Required for Driving: A Quasi-Experimental Trial[J]. Journal of Transport & Health, 2018, 9: 180-189. [23] HANI TABAI B, BAGHERI M, SADEGHI-FIROOZABADI V, et al. Evaluating the Impact of Train Drivers' Cognitive and Demographic Characteristics on Railway Accidents[J]. Safety Science, 2018, 110: 162-167. [24] MILAN V, BORIS A, DALIBOR P, et al. Testing the Psychophysical

Characteristics of Professional Drivers -Can We Identify Unsafe Drivers?[J]. Transportation Research Part F: Traffic Psychology and Behaviour, 2016, 42(1): 104-116. [25] 雷丽娜. 2018 年全国小汽车保有量首次突破 2 亿辆 [EB/OL]. [2019-01-13]. http://www.gov.cn/xinwen/2019-01/13/content_5357441.htm. (LEI Li-na. In 2018, the number of cars in China exceeded 200 million for the first time[EB/OL]. [2019-01-13]. http://www.gov.cn/xinwen/2019-01/13/content_5357441.htm.) [26] ROLISON J J, REGEV S, MOUTARI S, et al. What Are the Factors That Contribute to Road Accidents? An Assessment of Law Enforcement Views, Ordinary Drivers' Opinions, and Road Accident Records[J]. Accident Analysis and Prevention, 2018, 115(1): 11-24. [27] AMADO S, KOYUNCU M, KACA G. Comparison of Three Systems for Psychotechnical Assessment Used in Turkey[J]. Transportation Research Part F: Psychology and Behaviour, 2015, 32: 78-90. [28] ANIŢEI M, CHRAIF M, SCHUHFRIED G, et al. The Validation of Expert System Traffic Psychological Assessment to Romanian Driving Schools[J]. Procedia - Social and Behavioral Sciences, 2011, 30(1): 457-464. [29] ECKERT A, SEVENICH M, RIETH P E. Emergency Steer & Brake Assist - A Systematic Approach for System Integration of Two Complementary Driver Assistance Systems[J]. European Journal of Political Research, 2011, 50(4): 441-478. [30] FOY H J, PETER C. Mental Workload Is Reflected in Driver Behaviour, Physiology, Eye Movements and Prefrontal Cortex Activation[J]. Applied Ergonomics, 2018, 73: 90-99. [31] G. K, KOUNTOURIOTIS, N., et al. Leading to Distraction: Driver Distraction, Lead Car, and Road Environment[J]. Accident Analysis & Prevention, 2016, 89: 22-30. [32] YANG Y, CHEN J, EASA S M, et al. Driving Simulator Study of the Comparative Effectiveness of Monolingual and Bilingual Guide Signs on Chinese Highways[J]. Transportation Research Part F: Traffic Psychology and Behaviour, 2019. [33] LI W, HE Q C, FAN X M, et al. Evaluation of Driver Fatigue on Two Channels of EEG Data[J]. Neuroscience Letters, 2012, 506(2): 235-239. [34] CHEN J, WANG H, HUA C. Assessment of Driver Drowsiness Using Electroencephalogram Signals Based on Multiple Functional Brain Networks[J]. International Journal of Psychophysiology, 2018, 133: 120-130. [35] BELAKHDAR I, KAANICHE W, DJEMAL R, et al. Single-Channel-Based Automatic Drowsiness Detection Architecture with a Reduced Number of EEG Features[J]. Microprocessors & Microsystems, 2018, 58(1): 13-23. [36] FERGUSON C J. An Effect Size Primer: A Guide for Clinicians and Researchers[J]. Professional Psychology Research and Practice, 2009, 40(5): 532-538. [37] XIAO Q, HE R, YU J. Technology in Society Evaluation of Taxi Carpooling Feasibility in Different Urban Areas through the K-Means Matter e Element Analysis Method[J]. Technology in Society, 2018, 53: 135-143. [38] WANG M, LI L, JIN J. Decision-Making of Landslide Treatment Schemes Using Identical Degree of Set Pair Analysis[C]. 2009 CHINESE CONTROL AND DECISION CONFERENCE, ed.//International Conference on Chinese Control & Decision Conference. Guilin, China: 2009 Chinese Control and Decision Conference, 2009: 3875-3879. [39] WANG W S, JIN J L, DING J. A New Approach to Water Resources System Assessment——Set Pair Analysis Method[J]. Science in China(Series E:Technological Sciences), 2009, 52(10): 3017-3023. [40] TSUEI

H-J, TSAI W-H, PAN F-T, et al. Improving Search Engine Optimization (SEO) by Using Hybrid Modified MCDM Models[J]. Artificial Intelligence Review, 2018, 53: 1-16. [41] SABATER S, PASTOR-JUAN M R, ANDRES I, et al. MRI Prostate Contouring Is Not Impaired by the Use of a Radiotherapy Image Acquisition Set-up. An Intra- and Inter-Observer Paired Comparative Analysis with Diagnostic Set-up Images[J]. Cancer/Radiotherapie, 2021, 25(2): 107-113. [42] BAO D, ZHANG X. Measurement Methods and Influencing Mechanisms for the Resilience of Large Airports under Emergency Events[J]. TRANSPORTMETRICA A-TRANSPORT SCIENCE, 2018, 14(10): 855-878. [43] YANG C H, TAO H. Brittle Relationship Analysis of Human Error Accident of Warship Technology Supportability System Based on Set Pair Analysis[C]//2018 7th International Conference on Industrial Technology and Management (ICITM). . [44] LIU Y. Study on Environment Evaluation and Protection Based on Set Pair Analysis—A Case Study of Chongqing[J]. Energy Procedia, 2012, 14: 14-19. [45] YAN F, XU K. A Set Pair Analysis Based Layer of Protection Analysis and Its Application in Quantitative Risk Assessment[J]. Journal of Loss Prevention in the Process Industries, 2018, 55: 313-319. [46] TAO J, FU M, SUN J, et al. Multifunctional Assessment and Zoning of Crop Production System Based on Set Pair Analysis-A Comparative Study of 31 Provincial Regions in Mainland China[J]. Communications in Nonlinear Science and Numerical Simulation, 2014, 19(5): 1400-1416. [47] GE W, LI Z, LI W, et al. Risk Evaluation of Dam-Break Environmental Impacts Based on the Set Pair Analysis and Cloud Model[J]. Natural Hazards, 2020, 104(2): 1641-1653. [48] 李德顺. 基于广义集对分析的系统危险性评价研究 [D]. 东北大学, 2010. (LI De-shun. Research on System Risk Assessment Based on General Set Pair Analysis[D]. Northeastern University, 2010.) [49] 葛巍, 李宗坤, 李娟娟, et al. 改进的集对分析法在溃坝社会影响评价中的应用 [J]. 长江科学院院报, 2020, 37(1): 6. (GE Wei, LI Zong-kun, LI Juanjuan, et al. An Improvement on Set Pair Analysis and Its Application to Social Impact Assessment of Dam Breach[J]. Journal of Yangtze River Scientific Research Institute, 2020, 37(1): 6.)

*Note: Figure translations are in progress. See original paper for figures.*