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Research on Quantification Method of Driver Visual Load Based on Factor Analysis

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ABSTRACT: To investigate the impact of secondary driving tasks on driver visual load, eye movement indicators such as gaze, saccade, and pupil diameter under different secondary task loads were collected. Based on the eye movement characteristic index system, a factor analysis method was employed to construct a quantification model for driver visual load. The model results indicate that, compared to normal driving, the visual load of drivers performing mobile phone operations increased by 22.29%, while the visual load of drivers performing digit memory tasks decreased by 8.93%. Additionally, significant individual differences in visual load were observed among different drivers. The findings of this study can provide a reference for the development of driver assistance systems.

KEYWORDS: Traffic safety; Driving behavior; Visual load; Factor analysis.

I. INTRODUCTION

In the complex road traffic system composed of "human-vehicle-road-environment," human factors are widely recognized as the primary cause of traffic accidents. Among these, visual load, which is closely related to drivers' cognitive processing of information, has drawn significant attention due to its substantial impact on various driving behavior indicators [1].

When the visual environment is complex and the amount of information to be processed increases, drivers' visual search tasks become more demanding, leading to higher visual load [2]. Prolonged exposure to high visual load may result in dangerous driving behaviors, such as delayed reactions. Conversely, in simpler visual environments, the amount of information to be processed decreases, resulting in lower visual load. However, prolonged low visual load may induce visual fatigue [3]. Additionally, visual load is a key factor affecting drivers' information-processing capacity [4]. Therefore, quantifying drivers' visual load under different scenarios is crucial for driving safety assessment.

Existing research on driver visual load primarily focuses on analyzing eye movement indicators such as fixation, saccade, and pupil dynamics, which vary with driving conditions and tasks. Current evaluation methods for driver visual load mainly include:

1.Subjective assessment (e.g., NASA-TLX questionnaire [5]), which is susceptible to individual differences and is rarely used alone.

2.Multi-task method, which evaluates visual task difficulty and its impact on visual load based on secondary task error rates [6].

3. Physiological parameter measurement, primarily relying on eye-tracking metrics [7].

However, few studies have quantified visual load under different secondary task scenarios on highways. To address this gap, this study designed three types of secondary task driving experiments and applied factor analysis to construct a driver visual load evaluation model, analyzing the influence of secondary tasks on drivers' visual characteristics.





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II. EXPERIMENTAL DESIGN

The experiment was conducted using a driving simulator platform, with driving scenarios designed and generated via UC-win/Road software. Vehicle motion parameters (including ego and surrounding vehicles) were recorded at 10 Hz. A Tobii Glasses 2 eye tracker was used to record participants' gaze points, pupil area, fixation/saccade types, and duration at a sampling rate of 50 Hz (units in milliseconds).

The experiment adopted a 3×3 design, consisting of:

- Three car-following scenarios, where the lead vehicle exhibited different braking behaviors:
 - No braking (control group)
 - Moderate braking (deceleration: 1 m/s^2)
 - Emergency braking (deceleration: 3 m/s²)
- Three secondary driving tasks:
 - No secondary task (control group)
 - Rapid Serial Visual Presentation (RSVP) (mobile phone operation task)
 - Delayed Digit Recall (1-Back) (digit memory task)

A total of 46 participants were recruited, with 4 dropping out due to motion sickness or other reasons. The final sample consisted of 42 participants (24 male, 18 female), aged 22–61 years ($M = 32.1 \pm 10.0$). Among them, 19 were professional drivers (taxi, bus, and ride-hailing drivers), and 23 were non-professional drivers.

III. EYE MOVEMENT CHARACTERISTICS UNDER DIFFERENT SECONDARY TASKS

Drivers' visual behavior is primarily reflected in fixation, saccade, and pupil dynamics. Based on preprocessed eyetracking data, key metrics were extracted as shown in Table 1.

Туре	Metric	Unit		
	Proportion of total fixation duration (PTFD)	%		
Fixation	Average fixation duration (AFD)	ms		
	Fixations frequency (FF)	times/min		
Saccade	Average saccades velocity (ASV)	°/s		
	Average saccades amplitude (ASA)	0		
	Saccade frequency (SF)	times/min		
Pupil	Average pupil diameter (APD)	mm		

Table 1. Selected Eye Movement Metrics

Eye movement metrics were analyzed using SPSS 26.0, with a 3×3 repeated-measures ANOVA (three secondary tasks × three car-following scenarios as independent variables, eye movement metrics as dependent variables). The Greenhouse-Geisser correction was applied when Mauchly's sphericity test was violated, with a significance level of α = 0.05.

1) Fixation Metrics

- Total fixation duration (PTFD):
 - Significant main effect of secondary task (F = 3.936, p = 0.024).
 - PTFD under different conditions:
 - No secondary task: 53.21%
 - Mobile phone task: 50.94%
 - Digit memory task: 46.06%
 - During mobile phone tasks, drivers frequently shifted gaze between the phone and the road, leading to shorter average fixation durations but higher total fixation duration compared to the digit memory task (compensated by increased fixation frequency).





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- Average fixation duration (AFD):
 - \circ Significant main effect of secondary task (F = 12.991, p < 0.001).
 - AFD decreased significantly during mobile phone tasks, as drivers needed to process both phone digits and road information.
- Fixation frequency (FF):
 - Significant main effect of secondary task (F = 8.295, p < 0.001).
 - o FF increased notably during mobile phone tasks due to frequent gaze shifts.

2) Saccade Metrics

- Average saccade velocity (ASV) & amplitude (ASA):
 - Significant differences across tasks (ASV: F = 32.435, p < 0.001; ASA: F = 23.420, p < 0.001).
 - Mobile phone task: ASV and ASA increased significantly (vs. no-task condition), indicating rapid visual searches.
 - o Digit memory task: ASV and ASA decreased, suggesting reduced visual scanning.
- Saccade frequency (SF):
 - \circ Significant main effect of secondary task (F = 8.014, p = 0.002).
 - Mobile phone task: SF increased (high-frequency, rapid search mode).
 - Digit memory task: SF decreased (from 27.06 to 25.73 times/min), reflecting less visual resource allocation.

3) Pupil Dynamics

- Average pupil diameter (APD):
 - \circ No significant main effect of secondary task (F = 1.873, p = 0.155), indicating no notable differences across scenarios.

IV. QUANTIFICATION OF VISUAL LOAD BASED ON FACTOR ANALYSIS

To quantify driver visual load, the following steps were implemented:

- 1. Establishing Evaluation Metrics:
 - Metrics from Table 1 (fixation, saccade, and pupil dynamics) were selected to form the driver visual load evaluation index set.
- 2. Correlation Analysis:
 - A correlation analysis was performed to assess relationships between variables (Table 2).
 - Key findings:
 - PTFD showed significant positive correlations with AFD, FF, and SF (p < 0.01), but a negative correlation with ASV.
 - AFD was negatively correlated with FF, ASV, and SF.
 - ASA and ASV exhibited a strong positive correlation (r = 0.670*).
 - FF and SF demonstrated a very strong positive correlation ($r = 0.886^*$).

Table 2. Correlation Coefficients and Significance of Eye Movement Metrics

	PTFD	AFD	FF	ASA	ASV	SF	APD
PTED	1.000	0.346**	0.394**	0.003	-0.196**	0.346**	0.021
AFD		1.000	-0.528**	0.036	-0.246**	-0.505**	0.078
FF			1.000	-0.093	0.060	0.886^{**}	-0.056
ASA				1.000	0.670^{**}	-0.023	-0.071
ASV					1.000	0.099	0.088
SF						1.000	-0.170**
APD							1.000





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- 3. Factor Analysis Suitability Tests:
 - Kaiser-Meyer-Olkin (KMO) Test: KMO = 0.512 (marginally below the 0.6 threshold).
 - Bartlett's Test of Sphericity: $\chi^2 = 1279.51$, p < 0.001, confirming suitability for factor analysis.
- 4. Factor Extraction and Interpretation:
 - Communalities: All variables exceeded 0.85, except ASA (0.896) and ASV (0.880), indicating minimal information loss.
 - Eigenvalue Criterion: Four factors were extracted, explaining 92.371% of cumulative variance.
 - Rotated Component Matrix (Table 3):
 - Factor 1 (F1): High loadings on FF (0.963) and SF (0.941), reflecting information acquisition load.
 - Factor 2 (F2): Dominated by ASA (0.929) and ASV (0.894), representing visual search difficulty.
 - Factor 3 (F3): Linked to PTFD (0.910) and AFD (0.680), indicating visual attention level.
 - Factor 4 (F4): APD (0.993), representing pupil dynamics.

Table 3. Factor Component Matrix

andardized Variable	Pre-Rotation Components			Post-Rotation Components				
	1	2	3	4	1	2	3	4
Zscore(PTFD)	0.322	-0.474	0.779	0.021	0.321	-0.056	0.910	0.029
Zscore(AFD)	-0.656	-0.323	0.604	-0.088	-0.663	-0.063	0.680	0.010
Zscore(FF)	0.953	-0.135	0.064	0.110	0.963	-0.029	0.122	0.015
Zscore(ASA)	-0.008	0.783	0.507	-0.159	-0.086	0.929	0.111	-0.112
Zscore(ASV)	0.164	0.893	0.202	0.119	0.117	0.894	-0.223	0.129
Zscore(SF)	0.950	-0.072	0.075	-0.025	0.941	0.036	0.111	-0.117
Zscore(APD)	-0.170	0.013	0.091	0.977	-0.071	0.005	0.027	0.993

5. Factor Score Equations:

 $\begin{array}{l} F_1 = 0.129 Z_{PTFD} - 0.286 Z_{AFD} + 0.408 Z_{FF} - 0.058 Z_{ASA} + 0.046 Z_{ASPV} + 0.390 Z_{SF} + 0.027 Z_{APD} \\ F_2 = 0.037 Z_{PTFD} + 0.029 Z_{AFD} - 0.022 Z_{FF} + 0.576 Z_{ASA} + 0.522 Z_{ASPV} + 0.018 Z_{SF} - 0.002 Z_{APD} \\ F_3 = 0.661 Z_{PTFD} + 0.502 Z_{AFD} + 0.077 Z_{FF} + 0.161 Z_{ASA} - 0.091 Z_{ASPV} + 0.076 Z_{SF} + 0.013 Z_{APD} \\ F_4 = 0.040 Z_{PTFD} - 0.033 Z_{AFD} + 0.069 Z_{FF} - 0.123 Z_{ASA} + 0.128 Z_{ASPV} - 0.062 Z_{SF} + 0.968 Z_{APD} \end{array}$

- 6. Visual Load Score:
 - \circ The composite score was calculated using variance contribution rates as weights:

$$VL = \frac{1}{92.371} (34.033F_1 + 23.891F_2 + 19.739F_3 + 14.708F_4)$$
(1)

 \circ Scores were normalized to [0, 1] using min-max scaling:

$$VL_{ij}^{*} = \frac{VL_{ij} - \min(VL_{ij})}{\max_{0 \in i \notin n} (VL_{ij}) - \min_{0 \in i \notin n} (VL_{ij})} \ddagger \psi i = 1, 2, ..., n; j = 1, 2, ..., m$$
(2)

V. ANALYSIS OF VISUAL LOAD QUANTIFICATION RESULTS

The visual load scores computed by the factor analysis model were statistically analyzed across experimental scenarios, and the results are visualized in the **heatmap shown in Figure 1**.





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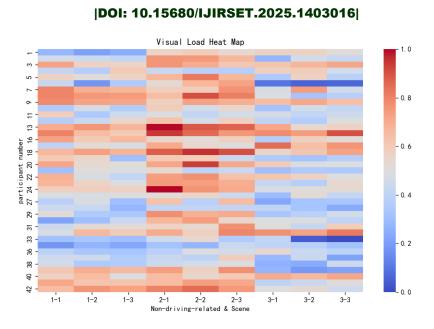


Figure 1. Heatmap of Driver Visual Load

Key Findings:

- 1. Effect of Secondary Tasks on Visual Load:
 - \circ Significant differences in visual load were observed across different secondary tasks (F = 28.292, p < 0.001), confirming that visual load varies dynamically with task complexity and driving conditions.
- 2. Individual Differences Among Drivers:
 - Under identical task and scenario conditions, drivers exhibited notable inter-individual variability in visual load.
 - High-load drivers (e.g., Subjects 13, 14, 18): Consistently displayed elevated visual load across all scenarios.
 - Low-load drivers (e.g., Subjects 33, 34): Demonstrated minimal fluctuations in visual metrics, suggesting better adaptive regulation of visual attention.

VI. CONCLUSIONS

To objectively quantify the visual load under secondary driving tasks, this study established an evaluation method based on factor analysis, incorporating eye movement metrics such as fixation, saccade, and pupil dynamics. By extracting common factors and weighting them according to their variance contribution rates, a comprehensive assessment of driver visual load was derived.

Key Findings:

- 1. Task-Dependent Visual Load Variations:
 - \circ Visual load exhibited significant differences across secondary tasks (p < 0.001), confirming that it dynamically adapts to task demands and driving scenarios.
 - Mobile phone tasks increased visual load by 22.29% (vs. baseline), while digit memory tasks reduced it by 8.93%, highlighting the divergent impacts of cognitive versus manual secondary tasks.
- 2. Individual Differences in Load Regulation:

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- Under identical conditions, drivers demonstrated marked inter-individual variability in visual load.
- High-susceptibility drivers (e.g., Subjects 13, 14, 18) consistently exhibited elevated load, whereas low-susceptibility drivers (e.g., Subjects 33, 34) maintained stable visual attention with minimal fluctuations.

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Practical Implications:

- The proposed factor analysis framework provides a robust tool for quantifying visual load, aiding the development of adaptive driver assistance systems tailored to individual cognitive profiles.
- Findings underscore the need for personalized safety interventions, such as workload-aware alerts or task scheduling, to mitigate risks for drivers with poor load regulation.

Limitations and Future Work:

- Sample diversity: Expanding demographic representation (e.g., age, driving experience) could enhance generalizability.
- Dynamic environments: Investigating visual load in real-world mixed-traffic conditions remains a critical next step.

This study advances the empirical understanding of driver visual load, bridging theoretical metrics with actionable insights for automotive safety.

VII. FUNDING

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