The "Pressure-State-Response" Pattern Analysis of Congestion-Involved Drivers

Praveen Isuram[1], Etikala Sainath[2], V.Krohith[3],
Associate Professor[1], Assistant Professor [2],
Student[3],
Department of Mechanical,
BRILLIANT GRAMMAR SCHOOL EDUCATIONAL SOCIETY'S GROUP OF INSTITUTIONS-INTEGRATED CAMPUS
**Abdullapurmet (V), Abdullapurmet (M), R.R Dt. Hyderabad-501505.**

ABSTRACT

The stress of driving in heavy traffic has become a major issue during rush hour in most Chinese cities. There is a need to investigate the connection between drivers' attitudes and behaviors and traffic congestion since there is so little data available on this topic at the moment. Furthermore, the pressure-state-response (PSR) model is developed to characterize that connection, for short. Here, the PSR framework has a three-tiered logical structure that includes the traffic congestion environment, a shift in drivers' physiology, and a shift in drivers' behavior. Different types of drivers were assigned to drive in heavy traffic according to the PSR framework, and then the status of the traffic flow, the drivers' physiological, and the drivers' behavioral traits were assessed using the proper instruments. The parameters of the PSR framework are also determined by an analysis of the driver's visual features and lane-changing characteristics. PSR provides the required rational room and systematic framework for traffic congestion management by identifying the evolving law of drivers' attributes in gridlock.

1. Introduction

In major cities, rush hour traffic has become a distinctive phenomenon due to the ever-increasing number of cars and the corresponding lack of public transit. The amenities are the primary cause [1]. Therefore, academics often examine the supply and demand for transportation while investigating the root causes, creation process, and mitigation techniques for traffic congestion. For the purpose of refining the conventional economic models of traffic congestion, Arnett [2] created a bathtub model of downtown rush-hour traffic. Using the macroscopic basic diagram, which represents resilient second-best optimum methods that may further minimize congestion externalities, Stokers and Geroliminis [3] investigated the connection between land use and traffic congestion. Scholars have proposed numerous models for traffic congestion prediction due to its significance in route guidance and traffic management [4, 5], including the nearest neighbor method [5, 6], the ARIMA (autoregressive integrated moving average) model [7], and the vector ARMA (autoregressive moving average) model [8, 9]. Congestion costs businesses billion annually and has a negative psychological effect on motorists [8]. Congestion raises drivers' blood pressure and mental workload, both of which contribute to reckless driving [9, 10]. Therefore, the mechanism underlying the genesis of rush-hour driving behavior may be seen in the "perception-judgment-decision" process. Statistics show that the visual system accounts for 70% of drivers' perceptual information and several researches have recorded and studied drivers' eye movements to back up this claim. Lansdowne [11] conducted a research in which drivers performed in-vehicle activities while visual allocation and verbal responses were collected to identify individual variations. A motorist must gaze at the right places in a traffic scene, according to Underwood et al. [12], so that they may learn about dangers and possible dangers there.

More frequent brief blinks were recorded by Benedetti et al. [13].
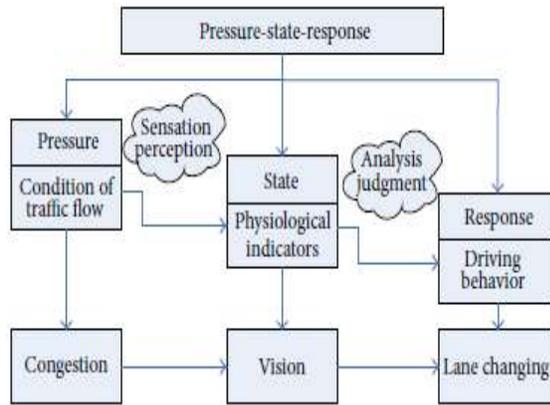
Driver "pressure-state-response" model (Figure 1).
With in-car infotainment system (IVIS) interaction while driving; longer blinks increase with longer commute times. Higher trait inclinations are associated with increased frequency and intensity of emotional states when driving in a variety of contexts [14]. It is unclear how a driver's propensity for rage when behind the wheel affects their actions.

Reports from angry motorists indicate that they are more likely to drive at greater speeds, less likely to obey the speed limits, have more near misses [15, 16], pay less attention to the road, and have less control over their vehicles [14, 15]. As a result, urban drivers' dispositions would suffer due to traffic congestion [8], which would show up in their gaze patterns and other aspects of their driving style.

This article makes an effort to probe the common link between crowded roads, distracted drivers, and the way our eyes travel.

2. ''Pressure-State-Response'' Model of Drivers in Traffic Congestion

Humans and all other biota coevolved with their surroundings, as determined by the PSR (pressure state- response) model established by Rapport et al. [17, 18] in 1979.Next, the PSR model was extensively utilized in evaluating sustainable land use, assessing land quality, assessing ecosystem health, and assessing ecological security [19, 20]. An enhanced PSR model, such as the one seen in Figure 1, may be used to characterize the interaction between drivers and the traffic environment in a congested condition. Therefore, this portion of the paper is dedicated to investigating the model's definition and structure for the enhanced PSR. The revised PSR model (pressure = traffic congestion,

state = eye movement, and reaction = lane change) requires a deeper understanding of the frame model in traffic congestion, which may be thought of as a three-tiered logical structure.

(1) Pressure-traffic congestion: drivers set out on a journey intending to achieve certain goals and hoping to go at a certain pace, but the congestion forces them to slow down. Driving to and from work every day may be stressful [21], especially in heavy traffic. Thus, the level of gridlock serves as a proxy for the strain. Drivers' visual characteristics, such as fixation point distribution, fixation duration, average saccade speed, average saccade acceleration, blink duration, and blink rate, can be used to measure state-eye movement, which is the change of drivers' physiological indexes under the condition of traffic congestion.

3. Source Pressure for Drivers in Traffic Congestion

Scuba divers' trip time and running speed slow down due to traffic; hence the pressure coefficient is t0 - TN. As a noun, press refers to the pressure those drivers in heavy congestion experience. During rush hour, the pressure coefficient t0tn press is a cumulative index that represents the product of divers' time and speed from t0 to TN. The following demonstrates this:

$$\chi_{press}^{t_0 - t_n} = \frac{\left(\int_{t=t_0}^{t_n} V_{off\text{-}peak}(t)\,dt - \int_{t=t_0}^{t_n} V_{rush}(t)\,dt \right)}{\int_{t=t_0}^{t_n} V_{off\text{-}peak}(t)\,dt}, \quad (1)$$

where the pressure coefficient of drivers is denoted by the symbol t0tn push on the S route between t0 and ten during rush hour, in kilometers; The velocities of vehicles on Route S during rush hour are represented as a function of time, denoted in kilometers per hour by Vrush(t); Where t is the time drivers spend in transit, in hours; t0 is the time drivers begin their journey on Route S in the morning; and tn is the time drivers finish their journey on Route S in the evening. The pressure coefficient in heavy traffic may be boiled down to the following according to its definition:

$$\chi_{press}^{t_0 - t_n} = \frac{\left[\overline{V}_{off\text{-}peak} \cdot (t_n - t_0) - \overline{V}_{rush} \cdot (t_n - t_0) \right]}{\left[\overline{V}_{off\text{-}peak} \cdot (t_n - t_0) \right]}, \quad (2)$$

$$\chi_{press}^{t_0 - t_n} = \frac{\left(\overline{V}_{off\text{-}peak} - \overline{V}_{rush} \right)}{\overline{V}_{off\text{-}peak}}, \quad (3)$$

Where Vrush is the mean speed of traffic along Route S during rush hour in kilometers per hour and Voff-peak is the mean speed of traffic along Route S outside of rush hour in kilometers per hour. Figure 2 displays the results of an analysis of one thousand responses to a draft of an evaluation questionnaire on traffic congestion, which is based on the definition of the pressure coefficient in traffic congestion. Pressure coefficient for the 85% cumulative frequency value is 0.65; thus, t0tn press = 0.65 can be treated as the threshold value to classify the road traffic volume state based on the statistical results of 1000 questionnaires fitted to normal distribution function (= 0.5087, = 0.1361, and R 2 = 0.9656). Increased traffic may be expected at t0tn 0.65.
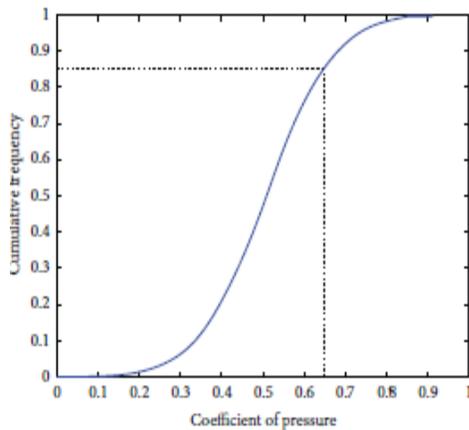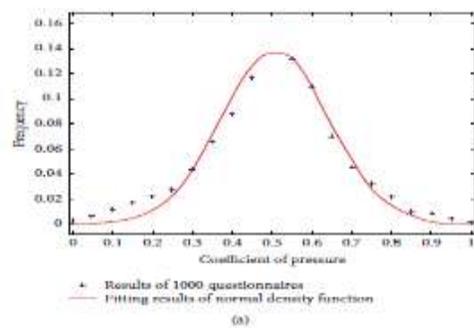

Figure 2 shows the assessment results of the pressure coefficient under heavy traffic.
Be considered to be in a condition of overall health, whereas t0tn if the pressure is more than 0.65, congestion has set in. Next, we'll examine how drivers' eyesight and lane-changing behaviors differ across the two conditions.

4. Driver's Visual Characteristics in Traffic Congestion

Experimentation Methodology 4.1. Thirty women and fifty men were hired as drivers (mean age = 33, min = 21, max = 50, SD = 8; mean age = 36, min = 21, max = 58, SD = 11). And educated on the bigger picture of the experiment's goals. All of them claimed to be in possession of current Chinese driver's licenses and had an average of nine years' worth of experience behind the wheel. Test scenarios of drivers' visual features are shown in Figure 3, and the dynamic visual characteristics of drivers are chosen as indications of "state" based on the pressure source of traffic congestion. All participants were made aware that they might stop participating at any moment (with no negative repercussions) if they felt uncomfortable. All participants completed the procedure of capturing data related to their eye movements and driving performance in both normal and congested conditions (the latter two are discriminated using formula (3) and the threshold value of t0tn push).

4.2. Eye Fixation
The Location of Fixing Points, 4.2.1. Coordinates reflect the spatial similarities and contrasts between fixation spots in the general and crowded condition.

Table 1 presents indices of drivers' general and congested visual features.

No.	Types of eye movements	Indexes of eye movements
1	Fixation	Fixation points' distribution
		Fixation duration
2	Saccade	Average saccade speed
		Average saccade acceleration
3	Blink	Blink duration
		Blink rate

Dispersal of focusing points. As can be seen in Figure 4, the horizon plane's x-axis is split into 800 units, while the y-axis is divided into 600 units. Figure 4 shows the whole situation. Divers tend to concentrate their fixations along the x-axis between 150 and 500 and the y-axis between 300 and 550 when visibility is good, but along the x-axis between 100 and 600 and the y-axis between 200 and 500 when visibility is poor. Therefore, in a crowded condition, the distribution of fixation sites spans 1.7 times the spatial range of dispersion in a non-crowded state. Time Spent Staring 4.2. Fixation length is a useful measure of how drivers are allocating their limited visual resources. Table 2 displays the findings of the statistical study. In a less crowded environment, the mean value and standard deviation of fixation time are both lower. Figures 5 and 6 show that, contrary to what could be expected
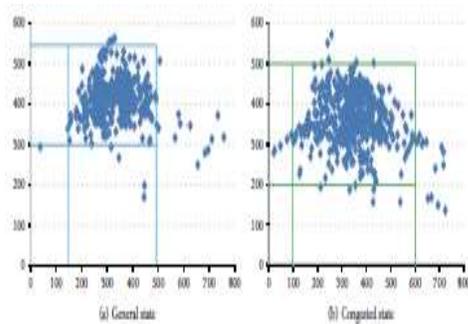
from a normal distribution, fixation duration and congestion follow a log-normal distribution.

4.3.3 Eye Blinking

The Typical Saccade Rate is 4.3.1 m/s. Table 3 displays the average saccade speed data from the statistical study of drivers.Themean

(a)   (b)   (c)

(d)   (e)   (f)

(g)   (h)   (i)

Figure 3: Test scenarios of driver's visual characteristics.

(a) General state   (b) Congested state

Characteristics of the planar distribution of drivers' fixation locations.

The mean saccade speed and its standard deviation are both larger in a crowded environment than in a less crowded one. As can be seen in Figures 7 and 8, the average saccade speed does not follow a log-normal distribution, even in the crowded condition. The Typical Acceleration of a Saccade is 4.3.2. Table 4 displays the average saccade acceleration data from a statistical examination of drivers. In a less packed environment, the average saccade acceleration has a higher mean value and a lower standard deviation. Acceleration typical of saccades
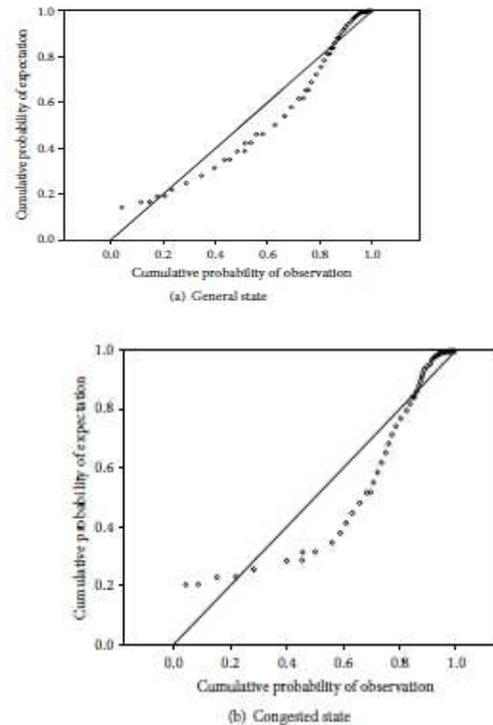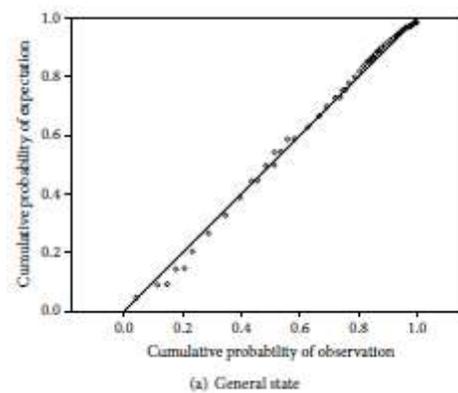

(a) General state

(b) Congested state

Figure 5: P-P figure of normal distribution fitting.

(a) General state

(b) Congested state
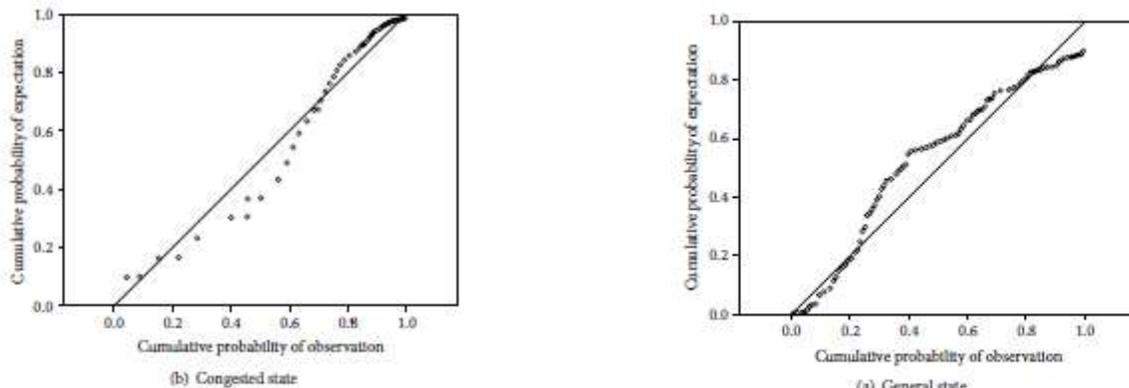
Figure 6: P-P figure of log-normal distribution fitting.

(a) General state

(b) Congested state
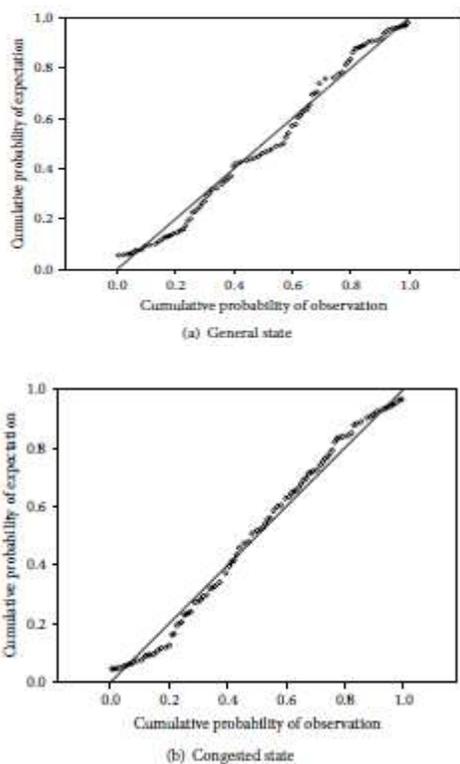
Figure 7: P-P figure of normal distribution fitting.
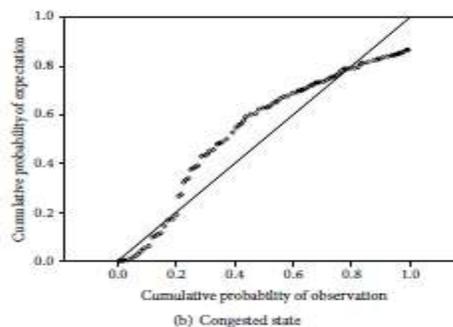

(a) General state

(b) Congested state

Figure 8: P-P figure of log-normal distribution fitting.

4.4. Eye Blink

Time between blinks (4.4.1). Table 5 shows the results of a statistical study of the length of time drivers' eyes were open. Figures 11 and 12 show that there is a general trend toward shorter blink durations. Additionally, congestion follows a log-normal distribution rather than a normal one. 4.4.2. Blink Frequency. Table 6 displays the findings of a statistical investigation of the blink rate of drivers. In a less crowded environment, the mean value and standard deviation of the blink rate are different. Figures 13 and 14 show that the blink rate in both its normal and congested states follows a normal distribution and a log-normal distribution, respectively. Test for Significance (4.5). Indicators of drivers' visual features did not exhibit normal distribution and variance homogeneity, as discussed above, and hence failed the parameter test. To determine whether or whether there is a statistically significant difference between markers of drivers' visual features in the normal and congested states, we use a nonparametric test (the Mann-Whitney U test). Table 7 shows that there are significant differences between the general and congested state indicators of drivers' visual attributes. There is a highly significant difference (P 0.01) between the indices for fixation

time and blink rate, a significant difference (P 0.05) between the indices for average saccade speed and blink duration, but no difference (P > 0.05) between the indices for average saccade acceleration. Therefore, our findings imply that drivers' visual qualities are significantly impacted by traffic congestion.

Table 2 shows the statistical findings on the time spent fixated.

No.	Sample	Average	Std.	Deviation	Kurtosis
1	General state	299	205	1.330	1.371
2	Congested state	271	229	1.550	1.486

Table 3: Results of statistical analysis on the average saccade speed.

No.	Sample	Average	Std.	Deviation	Kurtosis
1	General state	122	69	0.191	−0.972
2	Congested state	146	81	−0.033	−1.072

Table 4: Results of statistical analysis on the average saccade acceleration.

No.	Sample	Average	Std.	Deviation	Kurtosis
1	General state	8704	5958	0.050	−1.333
2	Congested state	9129	6510	0.043	−1.463

Table 5: Results of statistical analysis on the blink duration.

No.	Sample	Average	Std.	Deviation	Kurtosis
1	General state	212	97	0.736	−0.328
2	Congested state	202	94	0.856	−0.087

Table 6: Results of statistical analysis on the blink rate.

No.	Sample	Average	Std.	Deviation	Kurtosis
1	General state	0.25	0.05	0.341	−1.130
2	Congested state	0.22	0.05	−0.140	−0.935

Table 7: Difference significance for the indicators of drivers' visual characteristics.

No.	Index	General state		Congested state		Sig.
		Average	Std.	Average	Std.	
1	Fixation duration	299	205	271	229	0.000
2	Average saccade speed	122	69	146	81	0.019
3	Average saccade acceleration	8704	5958	9129	6510	0.553
4	Blink duration	212	97	202	94	0.023
5	Blink rate	0.25	0.05	0.22	0.05	0.006

5. Lane Changing Characteristics in Congested State

Varieties and Characteristics of Dangerous Lane Changes 5.1. Drivers feel the stress of going slowly in heavy traffic and are more likely to make a lane change or stop altogether. Lanes to facilitate safer driving and increased velocity.

Many drivers may resort to potentially dangerous lane switching habits when congestion pressure rises in an attempt to find breathing room. There are three distinct categories of unsafe lane changes based on these factors.

(1) Immediate lane switching: drivers move their cars into the desired lane without waiting for the headway to catch up. Such action constitutes dangerous lane switching that may lead to catastrophic collisions.

(2) Immediate importation into the target lane when sufficient headway has been acquired. Drivers continue to force their cars into the target lane even though the headway is insufficient. This is the type of dangerous lane switching that may spark disagreements. Third, if the headway does not satisfy the requirements, drivers may choose switch lanes so that their cars travel in parallel with those in the target lane as they progressively turn their vehicles in that direction. This is the type of erratic lane switching that may spark minor collisions. Table 8 shows statistical information on potentially hazardous lane changes across a variety of traffic conditions. Figures 15(a) and 15(b) show that the three forms of potentially dangerous lane changes are all affected by the same factors: traffic volume and speed. As traffic density and speed increase, drivers are more likely to switch lanes strategically, but they are less likely to switch lanes urgently. In the long run, the sweet spot between traffic density and speed is where the lane-changing % peaks. The Correlation between Dangerous Lane Changes and Accidents 5.2. Influences on potentially dangerous lane changes are categorized by a number of different categorization indices. Table 9 displays the number of traffic disputes per unit time at various observation stations and the frequency with which drivers engage in unsafe lane changes. X1, X2, and X3 are independent variables representing the frequency of direct lane change, pressed lane changing, and selected lane changing, respectively; Y is the dependent variable representing the number of traffic conflicts. Using regression analysis, data from Table 9 are used to create a linear model of traffic conflicts and the occurrence of various lane changes. Table 10 displays the model provided in formula (4) and its residual and standard residual values, which prove that the model meets the criteria.

$$Y = 2.5X_1 + 1.4X_2 + 0.53X_3 + 13.29. \qquad (4)$$

Behavior of lane changing directly has the largest impact on traffic conflicts, as measured by the absolute value of the effect coefficient for all types of unsafe lane changing behaviors. Impact on road safety, with studies showing that even one instance of a motorist abruptly switching lanes may increase the likelihood of a collision by a factor of 2.5. Accordingly, lane-selective driving had the smallest impact on road safety, with drivers experiencing on-average 0.53 times as many traffic conflicts after making just one lane-selective lane change.

(a) General state

(b) Congested state
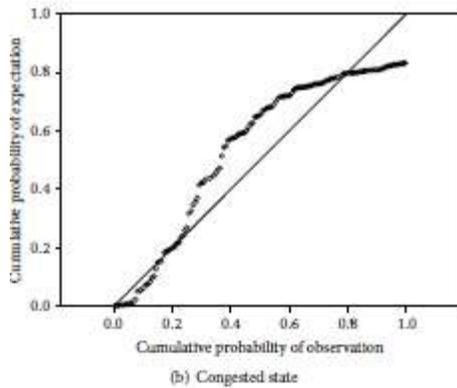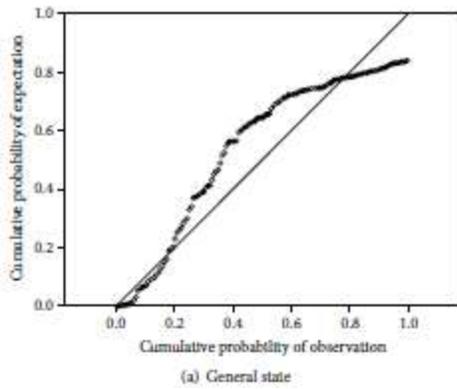
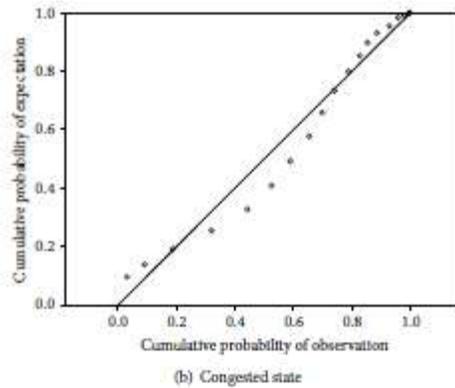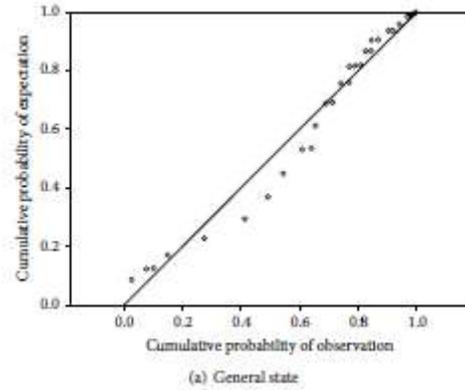**Figure 10: P-P figure of log-normal distribution fitting.**

(a) General state

(b) Congested state

Figure 11: P-P figure of normal distribution fitting.
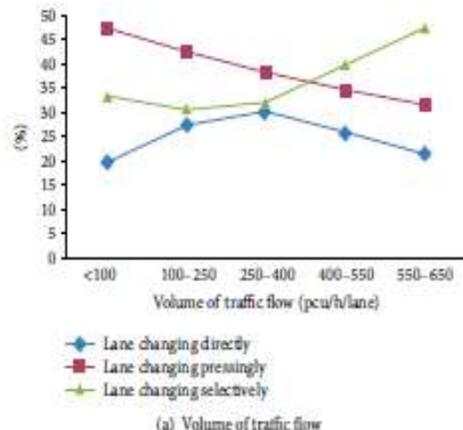

(a) General state

(b) Congested state
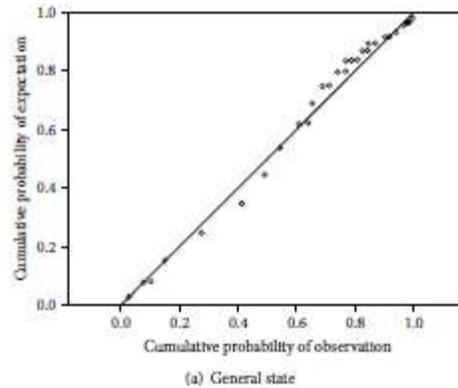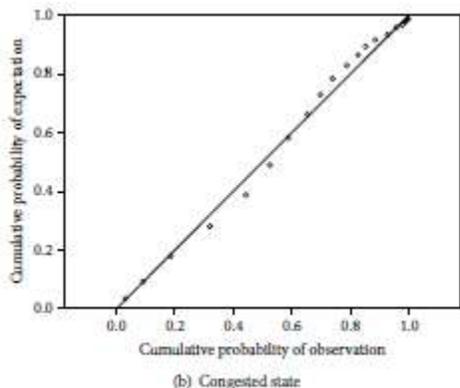
Figure 12: P-P figure of log-normal distribution fitting.

(a) Volume of traffic flow
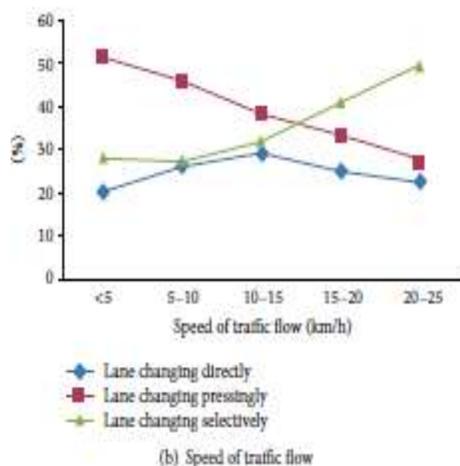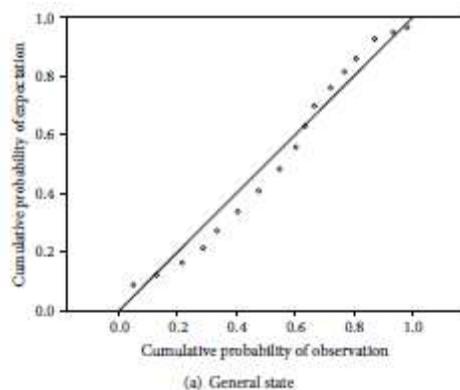

(a) General state

(b) Speed of traffic flow

Figure 15: Average weight of different risky lane changing behaviors in typical cities of China.
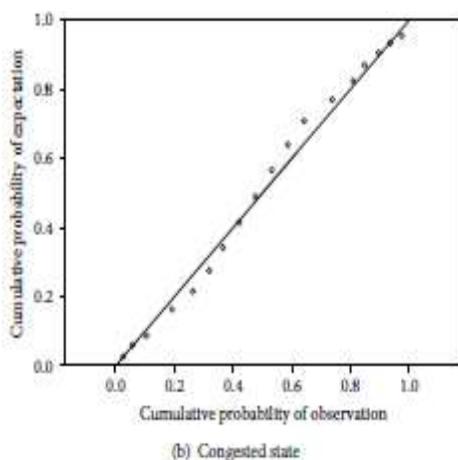
Table 8: Statistical analysis of risky lane changing behaviors via different traffic parameters.

Type of risky lane changing		Lane changing directly (%)	Lane changing pressingly (%)	Lane changing selectively (%)
Volume of traffic flow (pcu/h/lane)	<100	19.71	47.18	33.11
	100–250	27.31	42.34	30.35
	250–400	30.29	37.92	31.79
	400–550	25.78	34.55	39.67
	550–650	21.38	31.41	47.21
Speed of traffic flow (km/h)	<5	20.34	51.41	28.25
	5–10	26.52	46.13	27.35
	10–15	29.39	38.43	32.18
	15–20	25.21	33.63	41.16
	20–25	22.78	27.83	49.39

(b) Congested state

Figure 13: P-P figure of normal distribution fitting.

Table 9: Statistical analyses for frequencies of risky lane changing and number of traffic conflicts.

No.	Frequencies of risky lane changing behavior (times/h)			Traffic conflicts (times/h)
	Lane changing directly	Lane changing pressingly	Lane changing selectively	
1	35	23	18	143
2	32	18	27	108
3	18	29	15	107
4	16	22	23	96
5	28	16	23	119

Table 10: Value of residual and standard residual of formula (4).

Prediction Y	143.10	102.81	106.85	96.28	108.96
Residual	−0.0986	0.1899	0.1532	−0.2801	0.0357
Standard residual	−0.2555	0.4920	0.3968	−0.7257	0.0924

6. Conclusion

Traffic engineers and government officials should pay greater attention to drivers' physical and emotional well-being during traffic jams. Thus, the consequences of traffic jams in this study, we use the PSR model to quantify the effect that drivers' eye movement has on their lane-changing behavior and vice versa. Furthermore, the pressure coefficient has been defined to reflect drivers' perceptions of the level of traffic congestion; it has been proven, through adequate data analysis, that traffic congestion has a strong effect on drivers' visual characteristics; and the risky lane changing behaviors in traffic congestion have been specifically analyzed. Dynamic visual properties (distribution of fixation spots, length of fixation, average saccade speed, average saccade acceleration, blink duration, and blink rate) are compared using data collected during rush hour. Furthermore, it is shown that the typical and congested states have distinct eye movement characteristics. Video monitoring is used to gather information about potentially dangerous lane changes; the effects of these changes on traffic congestion have been categorized into three groups; and statistical methods are used to determine how frequently each group occurs. To further quantify the safety characteristics for dangerous lane shifting under the stress of traffic congestion, a linear connection between the amount of traffic conflicts and risky lane changing is constructed.

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