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Identification of Contributing Factors for Driver's Perceptual Bias of Aggressive Driving in China

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Abstract: Aggressive driving is common across the world. While most aggressive driving is conscious, some aggressive driving behavior may be unconscious on part of motor vehicle drivers. Perceptual bias of aggressive driving behavior is one of the main causes of traffic accidents. This paper focuses on identifying impact factors related to aggressive driving perceptual bias. Questionnaire data from 690 drivers, collected from a drivers' retraining course administered by the Traffic Management Bureau in Nanjing, China, were used to collect drivers' socioeconomic characteristics, personality traits, and external environment data. Actual penalty points were considered as an objective indicator and Gaussian mixture model (GMM) was used to cluster an objective indicator into different levels. The driving anger expression (DAX) was used to measure drivers' self-assessment of aggressive driving behavior and then to identify perceptual biases. Then a binary logistic model was estimated to explore the influence of different factors on drivers' perceptual bias of aggressive driving behavior. Results showed that bus drivers were less likely to have perceptual bias of aggressive driving behavior. Truck drivers, drivers with an extraversion characteristic, and drivers who have dissatisfaction with road infrastructure and actual work were likely to have a perceptual bias. The findings are potentially beneficial for proposing targeted countermeasures to identify dangerous drivers and improve drivers' safety awareness.

Keywords: aggressive driving behavior; perceptual bias; penalty points; Gaussian mixture model; binary logistic model

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1. Introduction

As reported by the World Health Organization [1], worldwide, 1.35 million people lost their lives on the roads in 2018. In China, the rapid growth of economy over the past few decades has significantly altered the transportation system. The number of vehicles has been increased and traffic accidents have emerged as a serious social and public management issue [2]. According to the China Statistical Yearbook, 2.06 people died per 10,000 motor vehicles [3]. Many previous studies used traffic accident analysis and traffic conflict analysis to explore the influencing factors of safety [4–7]. Among the various contributing factors of traffic accidents, aggressive driving has been shown to be positively related to traffic accidents [8–11].

Aggressive driving is defined as operating a vehicle in a selfish, pushy, or impatient manner, which could cause physical and/or psychological harm to other traffic participants [12–15]. While most aggressive driving is intentional, it is possible that some of it is unconscious on part of the drivers. A misperception of aggressive driving behavior is one of the main causes of traffic accidents [16]. Due to the confidence derived from the presence of modern vehicle safety features, some drivers may have formed unconscious or habitual aggressive driving behaviors [17]. Drivers with different socioeconomic attributes and personality traits may exhibit different perceptions of aggressive driving behaviors. [18]. A study investigating the influence of driver education and law enforcement on the perception of aggressive driving behaviors showed that many drivers were unaware of committing traffic violations or aggressive driving [19]. The findings confirmed the perceptual bias of aggressive driving, namely drivers are unaware of aggressive driving behavior.

Appropriate perception enables drivers to correctly attend to driving situations and as such, a driver's perception accuracy is helpful in dealing with unsafe situations in the driving environment. In this paper, by comparing the driver's self-assessment questionnaire with corresponding driving performance reflected by penalty points, the existence of perceptual bias was investigated. Furthermore, factors influencing the perceptual bias of aggressive driving are explored. Suggestions based on the findings are provided to reduce traffic violations in which perceptual bias may be a factor.

The structure of this paper is as follows. The next section provides an overview of the relevant literature. Section 3 presents the data collection procedure and methodology in data processing. Section 4 discusses empirical results while Section 5 concludes the paper by summarizing important findings and giving suggestions based on the findings.

2. Literature Reviews

2.1. Subjective Study of Aggressive Driving Behavior

The driving anger expression (DAX) classifies drivers' aggressive reactions into three categories: verbal aggressive expressions (e.g., cursing), physical aggressive expressions (e.g., hostile postures), and using vehicles to express anger (e.g., tailgating) [20]. The questionnaire is a commonly used method in analyzing the mechanism of aggressive driving and influencing factors. Many studies emphasize the relationship between aggressive driving and driver personality characteristics, such as pursuing sensory stimulation, preferring travel, and a high-stress trait, impulsivity, and hostility [21–24]. Drivers with tendencies to express aggression physically, callousness, impulsivity, and high sensation seeking can predispose an individual to aggressive driving behaviors [25,26]. In addition, socioeconomic attributes also affect aggressive driving, such as gender, age, social status, lifestyle, and interpersonal communication [27–31]. Some research show that the attitude of drivers, uncivilized behaviors of road users, road environment, and other pressures have influence on aggressive behavior [29,31–33]. A lack of police enforcement is a significant predictor of aggressive driving [34].

2.2. Objective Study of Aggressive Driving Behavior

Objective evaluation of aggressive driving behavior utilizes two methods. One is building models to analyze different driving styles based on data obtained from naturalistic driving studies (NDS), such as speed, acceleration, braking, and mechanical operation. Five categories of aggressiveness, from non-aggressive to very aggressive, were put forward [35]. Some scholars applied machine-learning models to evaluate driver's aggressive style between different characteristics using smartphone technology [36]. Lee and Jang used 43 taxis' in-vehicle driving records to evaluate aggressive driving behaviors and proposed three steps of a data analytic method [37]. Carlos et al. proposed a second-order representation, based on the bag-of-words' strategy, to model accelerometer timestamps associated with aggressive driving maneuvers. The results show that this novel representation outperformed both state-of-the-art works with 6% and 15% in F-measure for each scenario, respectively [38]. The other method is to evaluate a driver's aggressive driving behavior by experts. Based on the data obtained from simulator-based driving studies

(SDS) or NDS, and video data captured during driving, experts score the performance of a driver's aggressive driving to obtain the level of a driver's aggressive driving behavior.

2.3. Perceptual Bias

Perceptual bias of self-aggressive driving behavior occurs when a driver exhibits aggressive driving behavior but is unaware of it, resulting in a certain bias between the perceived behavior and the actual operational behavior. Research on perception bias asked drivers to compare their own skill to that of average drivers or their peers' through self-reported measures. Most drivers overestimated their driving skills [39–41]. However, a disadvantage of this method is that it does not compare subjective self-assessments with an objective measure of driving performance. Therefore, driver's self-assessment data should be verified by comparing it with data objectively measured in actual driving performance [42].

A verification approach is to compare driver's self-assessment with an expert's evaluation of driving behavior [43–45]. Such an approach revealed that young male drivers' self-assessments were inconsistent with their driving performance. This inconsistency varied with driving skill, driving experience and sensation-seeking propensity. However, this method is dependent on the skill of the experts, which may vary among the experts [45].

Another approach is to compare the driver's self-evaluation with vehicle operating data clustered into different levels in naturalistic driving or a driving simulator. Eboli et al. [46,47] revealed that perceptual bias does exist; drivers were not aware of their risk taking behavior. By examining old drivers' trip-specific driving patterns using objectively derived GPS measures of driving and comparing these patterns with drivers' self-reported information, results suggest that there was discrepancy between self-reported and objective measures [48]. Fountas provides further insights in the effect on the variations in cases when perceived and observed aggressive driving behaviors are present during the driving task, such as driver fatigue and external or internal distractions [49].

Previous studies have found that a relationship exists between a driver's poor driving performance and different types of traffic violations [8]. In addition, factors such as, demographic and socioeconomic characteristics (e.g., gender, age, income, etc.), traffic characteristics (e.g., traffic volume and traffic composition), and pavement conditions, were found having an influence on the level of aggressive driving behavior [17].

Considering that parts of the aggressive driving behavior are the results of perceptual bias and there is less attention on the investigation of influence factors on perceptual bias, this study have put forward objective methods that could avoid a self-defect in driver's aggressive behavior evaluation. Aggressive driving behavior was categorized into different levels by utilizing drivers' penalty points as an objective standard. The drivers' self-reported level of aggressive driving behavior from DAX provided subjective data. The presence of significant differences between subjective and objective levels would indicate the existence of perceptual bias.

3. Methodology

3.1. Participants

Drivers involved in unsafe driving in China are deducted certain points and are required to participate in retraining courses. Drivers with a greater number of traffic violations are more likely to have aggressive driving behaviors, mostly because of being overconfident in their driving skills [23]. Such drivers were the focus of investigation in this research.

Penalty point systems are used extensively for deterring drivers from committing traffic violations. Several countries have adopted such systems [8]. In China, the corresponding points are deducted for a different level of violations. The deducted points are usually 12 points, 6 points, 3 points, 2 points, and 1 point depending on the severity of a violation. Additionally, a driver may be penalized a maximum of 12 points in one year for various violations. If the accumulated penalty points of a driver are greater than or equal to 12 points in one year, the traffic management bureau suspends the driver's driving license. A driver then is required to attend a seven-day retraining course covering traffic safety laws and regulations. If the driver successfully completes the course, the penalty points are then waived and the driver's license is returned.

3.2. Measurement

The questionnaire included three parts. The first part recorded penalty points of drivers accrued in 6 months. Drivers were asked to fill in penalty points and the corresponding dates that each type of traffic violation occurred. The second part collected the driver's subjective perception data via a DAX questionnaire. The third part addressed questions about factors that would affect perceptual bias. In total, 13 items were designed to obtain socioeconomic attributes (age, gender, annual mileage, etc.), personality characteristics, and information on the external environment (employment/work, road, and vehicle environments).

Based on the driver's penalty points, the objective evaluation of driver's aggressive driving behavior was divided into three levels by the Gaussian mixture model (GMM [50]). The data obtained from the DAX scale represent the driver's subjective self-reported evaluation, which is divided into three levels in the questionnaire. Comparing the self-reported aggressive driving behavior levels with the objective classification results, this paper explored the presence of disparity between two evaluation results for drivers. A disparity between the two is indicative of driver perceptual bias.

3.2.1. Objective Evaluation of Aggressive Driving Behavior

Partial aggressive driving behaviors, including abnormal lane changes, speeding, running red lights, and threatening other travelers, are also traffic violations resulting in penalty points. Traffic violations were divided into aggressive traffic violations and other traffic violations. Other violations include failure to wear a seat belt, not carrying a driver's license, expired parking meter, etc. Since the purpose of this study was to analyze factors affecting drivers' perceptual bias of aggressive driving behavior, the data of the other driving behaviors mentioned above were not considered. The surveyed participants were studied at the retraining school; some on their first visit but some on their second and even third visits. The penalty points of each driver were concentrated at certain values. Accumulated penalty points of each driver for 6 months were collected, which regarded as a criterion to cluster driver's aggressiveness.

A GMM has been shown as an effective way for modeling data similar to this paper [51]. Theoretically, GMM is capable of characterizing data with any Gaussian distribution when the number of Gaussian components is large enough. For comparison with subjective data, the authors choose the three most important principle components. On this basis, GMM fits the distribution of the whole data by summarizing the distribution of three separate components. After applying GMM, the objective data, namely penalty points, were clustered into three clusters. As shown in Figure 1, 2–8 penalty points were regarded as the first level (M = 5.79, SD = 2.35), 9–16 were the second level (M = 12.74, SD = 1.67), and 17–25 were the third level (M = 19.88, SD = 3.05). Higher levels of penalty points indicate greater aggressive driving behavior.

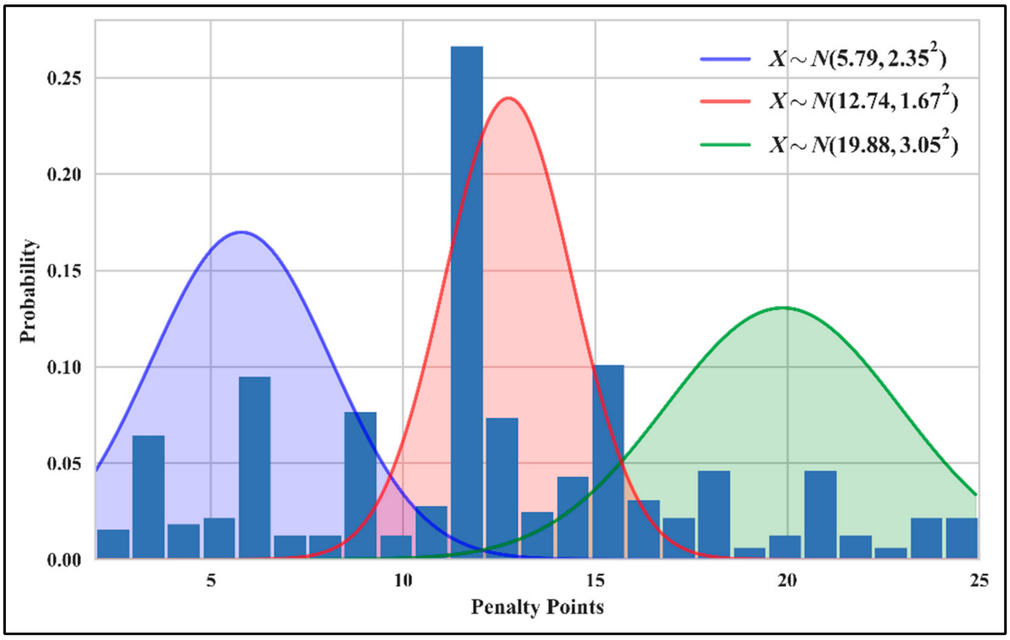

Figure 1. Objective classification of drivers' aggressive driving behaviors. Note: X~N() represents Gaussian distribution.

3.2.2. Subjective Assessment of Aggressive Driving Behavior

Aggressive driving behavior was measured by the DAX [20]. Each item of the DAX represented a potential aggressive driving experience that fit one of three types of situations: verbally aggressive expression, physically aggressive expression, and using a vehicle for aggressive expression. The DAX has demonstrated good internal reliability, with a Cronbach's α value for each subscale and a total score ranging from 0.80 to 0.92 [39]. For each item, participants reported how often they were involved in different types of driving behavior. A response on a five-point scale (1 = not at all; 3 = some; 5 = very often) was considered as a valid response. Subscale items were summed and then averaged. The item with higher scores indicated that a driver was more likely to engage in one type of aggressive driving. Verbally aggressive expressions, physically aggressive expression, and using the vehicle for aggressive expression were ranked as level 1, level 2, and level 3 on the increasing aggressive trend respectively. The DAX result was taken as the level of the driver's subjective perception of aggressive driving.

3.2.3. Drivers' Individual Characteristics

Socioeconomic attributes: Drivers' individual socioeconomic characteristics were measured, such as gender (coded as 0 = female and 1 = male), age in years (coded as 0 = 18–25, 1 = 26–35, 2 = 36–45, 3 = 46–55, 4 = 36–55, and 5 = older than 55), education level (coded as 0 = junior middle school, 1 = senior middle school, 2 = junior college, and 3 = postgraduate), monthly income (in RMB) (coded as 0 = less than 4000, 1 = 4000–8000, 3 = 8000–15,000, 4 = 15,000–20,000, and 5 = more than 20,000), driving years (coded as 0 = less than 3 years, 1 = 3–6, 2 = 6–10, 3 = 10–20, and 5 = more than 20), daily driving time (in hours) (coded as 0 = less than 1, 1 = 1–2, 2 = 2–4, 3 = 4–6, and 4 = more than 6), daily mileage (in km) (coded as 0 = less than 20, 1 = 20–50, 3 = 50–100, and 4 = more than 100), vehicle type (coded as 0 = car, 1 = MPV/SUV, 2 = bus, and 3 = truck), and professional driver (coded as 0 = no and 1 = yes).

Personality characteristics: Driver personality characteristics, including neuroticism, openness, conscientiousness, extraversion, and agreeableness, were measured using the Big Five scale, a self-reporting questionnaire developed by McCrae and Costa [52]. Each personality characteristics has its own feature. For example, traits of neuroticism include anxiety, hostility, and impulsiveness; conscientiousness traits include order, dutifulness, and self-discipline; and agreeableness traits include trust, altruism, and compliance [52]. Every respondent was assumed to have only one main personality characteristic. Sub-scale items of the Big Five scale were aggregated; the type of personality characteristics with the highest scores implied that the corresponding personality characteristics were more prominent.

External environment: Factors related to the external environment were measured using three items: work, road, and vehicle. Each item was reflected by two questions. For the work environment, the questions were "Are you content with your present job?" and "Are you satisfied with your work income?". For the road environment, the questions were "Are you satisfied with the road infrastructure (road pavement, traffic signs) that you often pass by?" and "Are you satisfied with traffic conditions of the roads you often pass by?". Five-point Likert scales ranging from 1 = "strongly agree" to 5 = "strongly disagree" were used in all of the above questions. For the vehicle environment, the questions were "how often do you listen to the voice prompt in the car while driving?" and "how often do you have people in your car?". A five-point scale ranging from 1 = "very often" to 5 = "not very often" was used for responses to this question. "Dissatisfaction with actual work", "Dissatisfaction with road infrastructure and condition", and "Not very often listen to the voice prompt and have people in car" were then used in the study.

3.3. Procedures

The Nanjing Traffic Management Bureau helped with administration of the field survey questionnaire. Data were collected from candidates who took part in the driver retraining course. Drivers in the course changed groups once a week, with approximately 150 drivers in each group. The investigation lasted for more than one month (five times), with four researchers assisting each time. Before each survey, the purpose of study was explained to drivers in detail; 730 initial responses were received from drivers who desired to participate in the study. Some responses were unrealistic, for example, the same option was chosen for all answers on one of the questionnaires. Such responses were removed resulting in a sample size of 690 for subsequent analysis.

3.4. Prototype Model

The binominal logistic model was selected in this study. Logistic regression is a probabilistic non-linear regression model, which is a method for analyzing the relationship between a binary variable y and influencing factors x. The independent variable x is called an exposure factor, and it can be a continuous or category variable [53]. The binominal logistic model was developed to predict a binary dependent variable as a function of a series of predicting variables, and has been widely used in driving behavior studies [54].

In the proposed model, the dependent variable is the existence of perceptual bias. $y = 1$ denotes perceptual bias and $y = 0$ denotes no perceptual bias. The model form is given by

$$logit\left(\frac{p_i}{1-p_i}\right) = b + \alpha_1 x_1 + \alpha_2 x_2 \cdots + \alpha_i x_i \cdots + \alpha_n x_n \tag{1}$$

where p_i is the probability that an event occurred; x_i represents a vector of independent variables for individual i, with a vector of α_i as the corresponding coefficients; and b is the intercept for the model.

The conditional probability of events that occurred is then given by

$$p_i = p(y_i = 1 | x_1, x_2, \cdots, x_n) = \frac{\exp(b + \alpha_1 x_1 + \alpha_2 x_2 \cdots + \alpha_i x_i \cdots + \alpha_n x_n)}{1 + \exp(b + \alpha_1 x_1 + \alpha_2 x_2 \cdots + \alpha_i x_i \cdots + \alpha_n x_n)} \tag{2}$$

The existence of a significant relationship between the independent and dependent variables is estimated by an iterative modeling process [55]. In the process, according to the probability-of-score test, explanatory variables entered the equation in sequence; and the variables were removed by the results of a partial-likelihood-ratio test; that is, those variables that were not significant at a 90% confidence level were excluded from the model. In order to explore the heterogeneity of variables, random effect, and random parameters were set up in the model [56].

4. Results and Discussion

4.1. Data Description

Table A1 (please see Appendix A) summarized the individual characteristics of the surveyed drivers. The sample comprised of 89.3% male and 10.7% female drivers. Most of the participants ranged in age from 26 to 45 years; 16.5% of the drivers had less than 3 years of driving experience. Moreover, most drivers in the sample were not professional drivers (78.6%). Almost half of the drivers had a monthly income between 4000 and 8000 RMB. Most of the drivers' educational levels were senior middle school and junior college, accounting for 74.8% of the respondents. Additionally, most drivers drove up to 100 km daily (30.1%). The passenger car was the most commonly used compared to other vehicle types (79.1% vs. 21.9%). As for drivers' personality characteristics, 46.1% of the respondents were agreeableness.

Table 1 summarizes the subjective and objective evaluation results of the aggressive driving behavior. Self-perceptual aggressive drivers at level 1 were 68.1% while, according to penalty points, only 22.3% of the drivers' aggressive driving behaviors were rated as level 1. Similarly, 60.0% of the drivers' objective evaluation of aggressive driving behavior was categorized as level 2. Taking penalty points as criterion, there are 76.6% of the respondents underestimated their aggressive driving behavior indicating widespread perceptual bias of aggressive driving behavior.

Table 1. Results of aggressive driving behavior evaluated subjectively and objectively.

Attribute	Range	Frequency	Percent	Perceptual Bias	
				Frequency	Percent
The DAX	Verbally aggressive expression	470	68.1%	360	76.6%
	Physically aggressive expression	104	15.1%	46	44.2%
	Using the vehicle for aggressive expression	116	16.8%	88	75.9%
Penalty points	2–8 (level 1)	154	22.3%	-	-
	9–16 (level 2)	414	60.0%	-	-
	17–25 (level 3)	122	17.7%	-	-

Statistics of the external environment show that the average satisfaction of drivers with the work environment was 2.45 (M = 2.45, SD = 0.91, where M denotes mean and SD standard deviation), which implies drivers were neutral on the work environment. The driver's average satisfaction with the road environment was 2.70 (M = 2.70, SD = 0.73) indicating that they were slightly dissatisfied with the road environment. In addition, responding drivers rarely used the in-vehicle voice prompt system and often drove alone (M = 4.05, SD = 0.903).

4.2. Model Estimation

Model estimation utilized statistical software SPSS (Version 20.0) and R language. Note that there were both continuous and categorical variables among the 13 independent variables in this study. The categorical variables that had more than two levels were set as dummy variables. According to the attribute of these factors, the variables with only "0" or "1" were constructed. The reference groups were selected first and the k levels of the categorical variable were set to $k - 1$ design variables.

Table 2 presents the results of the preanalysis process, which evaluates whether the variables are statistically significant by a score test ($p \leq 0.05$). Examining the results in

Table 2, four variables were statistically not significant, including gender, monthly income, driving years, and daily driving time. Nine independent variables were statistically related to drivers' perceptual bias.

Table 2. Score-test analysis of independent variables.

Independent Variable.	Score	df	Sig.
Gender	1.876	1	0.171
Age (base: 18–25)	14.653	4	0.005
26–35	0.425	1	0.514
36–45	3.081	1	0.079
46–55	2.753	1	0.097
More than 55	10.110	1	0.001
Education level (base: junior middle school)	10.942	3	0.012
Senior middle school	3.886	1	0.049
Junior college	9.675	1	0.002
Undergraduate	0.377	1	0.539
Monthly income (RMB) (base: less than 4000)	5.516	4	0.238
4000–8000	1.697	1	0.193
8000–15,000	0.125	1	0.724
15,000–20,000	0.294	1	0.588
More than 20,000	1.066	1	0.302
Driving years (base: less than3)	3.066	4	0.547
3–6	1.518	1	0.218
6–10	2.179	1	0.140
10–20	0.218	1	0.641
More than 20	0.046	1	0.830
Daily driving time (base: less than 1)	6.726	4	0.151
1–2	3.755	1	0.053
2–4	1.267	1	0.260
4–6	0.994	1	0.319
More than 6	1.199	1	0.273
Daily mileage (km) (base: less than 20)	9.425	3	0.024
20–50	2.925	1	0.087
50–100	2.162	1	0.141
More than 100	2.690	1	0.101
Vehicle type (base: car)	14.655	3	0.002
MPV/SUV	0.636	1	0.425
Bus	13.282	1	<0.001
Truck	1.069	1	0.301
Professional driver	8.242	1	0.004

Table 2. *Cont.*

Independent Variable.	Score	df	Sig.
Personality characteristics (base: agreeableness)	15.106	4	0.004
Neuroticism	1.192	1	0.275
Openness	9.725	1	0.002
Conscientiousness	0.142	1	0.706
Extraversion	0.199	1	0.655
Not very often listen to the voice prompt and have people in car	4.321	1	0.038
Dissatisfaction with road infrastructure and condition	12.861	1	<0.001
Dissatisfaction with actual work	8.917	1	0.003

In order to fully understand the impact of different factors on the perception bias, Table A2 (please see Appendix A) shows the model results that include both significant and non-significant variables. The random effect model and random parameters model were also developed. The DIC of the three models were 216.087, 214.126, and 215.811 respectively. It indicates that the random effect model had a relatively better model performance than the logit model and the random parameters model. Hence, the following discussion was based on the results of the random effect model.

4.3. Discussion

4.3.1. Socioeconomic Characteristics

Table A2 shows that age, daily mileage, vehicle type, and professional driver or not were significant variables that had an effect on the perceptual bias of aggressive driving behavior. The coefficient of people aged 26–35 was positive indicates that people aged 26–35 were more likely to have a perception bias than people aged 18–25. This might be due to the sample data, in which there were few people under 25 years old. It is notable that people aged 26–35 was found to be a random variable, which means that there were heterogeneous influences in this group. Although the other categories of the variable age were not significant, it still shows a positive trend that people aged 36–45, 46–55, and more than 55 were more likely to have a perception bias than people aged 18–25. There might be also due to the sample data.

The coefficient of daily mileage was negative, which indicates that it is less likely for people whose daily mileage is 20–50 and more than 100 to be involved in a perceptual bias of aggressive driving behavior. Although the variables "daily mileage is 50–100" was not significant, it shows a similar trend. The reason might be that drivers with more daily mileage could be more experienced, thus being more conscious with their perception of aggressive driving behavior.

The vehicle type "trucks" had statistically significant impact on perceptual bias of aggressive driving behavior. The estimated coefficient of truck drivers was positive. This might be due to relatively large blind spots around trucks. In addition, truck drivers were widely found in the state of fatigue. Research shows that owing to the length of journeys and the limited transportation time, some truck drivers try hard to rush to their destinations, which leads to excessive fatigue and a lack of concentration [57]. Therefore, perceptual bias is expected in self-aggressive driving behavior amongst truck drivers. However, the coefficient of the bus was negative indicating that bus drivers were less likely to have perceptual bias of aggressive driving behavior than passenger car drivers. This might be because bus drivers are held to higher driving standards. The driving examination for bus drivers is the most difficult, which makes a bus driver more responsible and assesses driving behavior more appropriately to ensure safe driving.

In addition, drivers who are professional are less likely to be involved in perception bias than others. One possible reason is that professional driver training is stricter and they are more experienced.

4.3.2. Personality Characteristics

Considering the influence of personality characteristics on perceptual bias in the modeling process, personality characteristics was modeled as four virtual variables based on the Big Five scale proposed by McCrae and Costa [58]; agreeableness was taken as the reference group. The results in Table A2 show that extraversion has a significant effect on drivers' perceptual bias of aggressive driving behavior. The coefficient of the variable was positive implying that the ratio of extraversion to the perceptual bias of aggressive driving behavior was more than that of a responsible personality characteristic. People with extraversion were more confident and likely to stimulate adventure. These emotions affected a driver's psychology and were likely reflected in aggressive driving behavior. This is consistent with previous studies showing that drivers were more likely to drive aggressively when they were overly impulsive and preferred stimulation [59,60]. However, drivers in such cases did not realize that they had already produced aggressive driving behavior, due to perceptual bias, leading to traffic violations and potential traffic accidents.

4.3.3. External Environment

Vehicle environment affected a driver's perceptual bias of aggressive driving behavior. The estimated coefficient for the variable "Not very often listen to the voice prompt and have people in car" was positive, which indicated that drivers preferring a voice prompt system were more likely to have a correct assessment of their driving behavior, while those driving alone were more likely to have a perceptual bias. It is notable that "Not very often listen to the voice prompt and have people in car" was also found to be a random parameter, which means that drivers may have different perceptions of passengers and the voice in the car. Hence, perhaps some drivers are more aware of their environment when listening to voice prompts from a navigation system. Some others are easily distracted by sound, which in turn leads to perception deviation.

Road environment also had a significant relationship with drivers' perceptual bias in aggressive driving behavior. Road infrastructure and traffic conditions were important factors affecting driving behavior [61]. The estimated coefficient of the variable "Dissatisfaction with road infrastructure and condition" was positive; that is, being less satisfied with the infrastructure or encountering a substandard road environment was more likely to impel drivers to have perceptual bias of aggressive driving behavior.

Although the work environment was not a significant factor for a driver's perceptual bias of aggressive driving behavior. The positive coefficient of the variable indicates that the greater dissatisfaction with the work environment was associated with greater levels of perceptual bias of the aggressive driving behavior. The reason could be that the work dissatisfactions turn into aggressive driving perhaps to offset inner negative emotions but without any realization.

5. Conclusions

Based on the driver's subjective assessment of aggressive driving and the objective evaluation of aggressive driving reflected by the driver's penalty points, a binary logistic regression model was estimated to analyze factors affecting drivers' perceptual bias of aggressive driving behavior, including individual socioeconomic attributes, personality characteristics, and information on external environment. Results are as follows:

(a) Truck drivers were more likely to have perceptual bias of aggressive driving behavior;
(b) Drivers with extroverted personalities were more likely to engage in perceptual bias;
(c) Less comfortable work or road environments promoted drivers' involvement in a perceptual bias of aggressive driving behavior and;

(d) Voice prompt systems and presence of passengers were helpful to a driver correctly assessing their driving behavior.

Based on these findings some suggestions to reduce driver's perceptual bias of aggressive driving behavior in the perspective of the transportation agencies and drivers are presented next. Transportation agencies responsible for the safety of the traveling public should strengthen traffic safety publicity and education to raise driver's safety awareness. Effective measures include conducting "face-to-face" educational activities and broadcasting educational films on accident causes resulting from perceptual bias. Transportation agencies could also perform oversight on companies providing transportation freight services and rectify the problem of long driving hours to reduce the perceptual bias of truck drivers. Based on the actual industry situation, private transportation companies could cooperate with public agencies to formulate psychological health evaluation standards for newly recruited drivers. In addition, comfortable road environment would reduce perceptual bias of aggressive driving behavior. Transportation agencies should maintain and update traffic facilities in a timely fashion. Measures to promote smooth traffic, such as green waves, tidal lane, and traffic police assistance are some of the options available for reducing aggressive driving. Considering that drivers do not seriously assess their driving behavior, it may be necessary to increase the financial penalties associated with violations and the seriousness of laws to lead drivers to better comply with the rules. This may be accomplished by promoting reformation of the violation mechanism and increasing the incentive policy for drivers without violations (e.g., reward drivers with no violations over the course of 1 year). Another way is to enhance the requirements of the driver's license examination, as it will also be helpful in increasing the driver's awareness of driving discipline.

Drivers should pay more attention to the problem of perceptual bias of aggressive driving behavior. Keeping a good mood while driving is beneficial for reducing the occurrence of traffic accidents caused by perceptual bias. Many people are under heavy work pressure and have more aggressive emotions [10]. Drivers may be encouraged to not drive alone as the presence of other passengers reduced aggressive driving behavior. Furthermore, drivers could install and apply multifunction voice assistant systems to keep an accurate perception of the surroundings.

On account of the limited time and labor resources, the data were only collected from one city in China (Nanjing). Due to differences in culture and driving behavior, findings may be different if this study is repeated in other cities or countries. In addition, the authors only analyzed factors affecting the perceptual bias of aggressive driving behavior. The influence of different levels of perceptual bias should be analyzed in future research. Furthermore, the basic hypothesis of this study is the Swiss cheese model [62,63], future work will provide further insights in road users perception evolution in terms of the Swiss cheese model. Additionally, each respondent in this study was assumed to have only one main personality characteristic. Additionally, future work will further explore the heterogeneity among the respondents. Despite these limitations, the experimental design, modeling framework, and results should be helpful to researchers in carrying further analysis.

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Appendix A

Table A1. Drivers' individual characteristics.

Attribute	Range	Frequency	Percent	Perceptual Bias	
				Frequency	Percent
Gender	Male	616	89.3%	436	70.8%
	Female	74	10.7%	58	78.4%
Age	18–25	74	10.7%	54	73.0%
	26–35	288	41.7%	210	72.9%
	36–45	180	26.1%	138	76.7%
	46–55	128	18.6%	84	65.6%
	More than 55	20	2.9%	8	40.0%
Education level	Junior middle school	148	21.4%	98	66.2%
	Senior middle school	256	37.1%	172	67.2%
	Junior college	260	37.7%	204	78.5%
	Undergraduate	26	3.8%	20	76.9%
Monthly income (RMB)	Less than 4000	92	13.3%	58	63.0%
	4000–8000	344	49.9%	254	73.8%
	8000–15,000	154	22.3%	112	72.7%
	15,000–20,000	48	7.0%	36	75.0%
	More than 20,000	52	7.5%	34	65.4%
Driving years	0–3	114	16.5%	80	70.2%
	3–6	170	24.6%	128	75.3%
	6–10	184	26.7%	124	67.4%
	10–20	156	22.6%	114	73.1%
	More than 20	66	9.6%	48	72.7%
Daily driving time (hour)	Less than 1	132	19.1%	100	75.8%
	1–2	176	25.5%	116	65.9%
	2–4	168	24.3%	126	75.0%
	4–6	84	12.2%	64	76.2%
	More than 6	130	18.8%	88	67.7%
Daily mileage (km)	0–20	118	17.1%	94	79.7%
	20–50	160	23.2%	106	66.3%
	50–100	204	29.6%	154	75.5%
	More than 100	208	30.1%	140	67.3%
Vehicle type	Car	546	79.1%	390	71.4%
	MPV/SUV	96	13.9%	72	75.0%
	Bus	10	1.4%	2	20.0%
	Truck	38	5.5%	30	78.9%

Table A1. *Cont.*

Attribute	Range	Frequency	Percent	Perceptual Bias	
				Frequency	Percent
Professional driver	Yes	148	21.4%	92	62.2%
	No	542	78.6%	402	74.2%
Personality characteristics	Agreeableness	318	46.1%	208	65.4%
	Neuroticism	182	26.4%	136	74.7%
	Openness	128	18.6%	106	82.8%
	Conscientiousness	24	3.5%	18	75.0%
	Extraversion	38	5.55%	26	68.4%

Table A2. Model results with significant and non-significant variables.

Variable	Logit Model			Random Effect Model			Random Parameters Model		
	Mean	**S.D.**	**[10%, 90%]**	**Mean**	**S.D.**	**[10%, 90%]**	**Mean**	**S.D.**	**[10%, 90%]**
Age (base: 18–25)									
26–35 *	1.046	0.690	[0.178, 1.960]	1.019	0.672	[0.199, 1.893]	1.017	0.658	[0.177, 1.85]
Standard deviation of parameter							0.029	0.01	[0.015, 0.045]
36–45	0.257	0.611	[−0.505, 1.036]	0.255	0.601	[−0.531, 1.017]	0.246	0.608	[−0.561, 1.015]
46–55	0.197	0.604	[−0.588, 0.981]	0.189	0.604	[−0.564, 0.941]	0.209	0.603	[−0.547, 0.974]
More than 55	0.097	0.543	[−0.547, 0.933]	0.083	0.543	[−0.534, 0.899]	0.107	0.534	[−0.525, 0.921]
Education level (base: junior middle school)									
Senior middle school	0.479	0.592	[−0.246, 1.237]	0.494	0.586	[−0.296, 1.219]	0.486	0.585	[−0.239, 1.272]
Junior college	0.096	0.609	[−0.644, 0.876]	0.127	0.608	[−0.677, 0.937]	0.134	0.624	[−0.682, 0.922]
Undergraduate	1.126	1.341	[−0.489, 2.834]	1.119	1.286	[−0.501, 2.768]	1.17	1.385	[−0.610, 2.952]
Monthly income (RMB) (base: less than 4000)									
4000–8000	−0.513	0.72	[−1.476, 0.391]	−0.551	0.723	[−1.519, 0.349]	−0.532	0.744	[−1.524, 0.403]
8000–15,000	−0.627	0.849	[−1.744, 0.479]	−0.623	0.817	[−1.673, 0.440]	−0.657	0.858	[−1.781, 0.440]
15,000–20,000	1.018	1.316	[−1.403, 2.787]	0.937	1.261	[−0.629, 2.553]	0.984	1.315	[−0.615, 2.725]
More than 20,000	−1.116	0.909	[−2.907, 0.039]	−1.147	0.923	[−2.294, 0.062]	1.106	0.937	[−2.327, 0.013]
Daily mileage (km) (base: less than 20)									
20–50 *	−0.898	0.683	[−1.746, −0.041]	−0.877	0.689	[−1.733, 0.012]	−0.852	0.673	[−1.752, −0.027]
50–100	−0.674	0.661	[−1.484, 0.155]	−0.702	0.666	[−1.551, 0.141]	−0.664	0.669	[−1.532, 0.204]
More than 100 *	−1.522	0.746	[−2.469, −0.558]	−1.514	0.732	[−2.447, −0.579]	−1.468	0.716	[−2.41, −0.594]
Vehicle type (base: car)									
MPV/SUV	0.124	0.573	[−0.586, 0.890]	0.097	0.577	[−0.659, 0.885]	0.13	0.565	[−0.57, 0.849]
Bus	−0.501	1.515	[−2.336, 1.429]	−0.628	1.436	[−2.362, 1.218]	−0.576	1.434	[−2.429, 1.262]
Truck *	1.354	0.898	[0.136,2.491]	1.329	0.848	[0.215,2.405]	1.325	0.867	[0.225,2.483]
Professional driver *	−0.898	0.665	[−1.747, −0.046]	−0.896	0.658	[−1.752, −0.081]	−0.875	0.648	[−1.685, −0.066]

Table A2. *Cont.*

Variable	Logit Model			Random Effect Model			Random Parameters Model		
	Mean	**S.D.**	**[10%, 90%]**	**Mean**	**S.D.**	**[10%, 90%]**	**Mean**	**S.D.**	**[10%, 90%]**
Personality characteristics (base: agreeableness)									
Neuroticism	0.358	0.226	[0.080, 0.654]	0.371	0.232	[0.088, 0.677]	0.341	0.215	[0.061, 0.616]
Openness	0.247	0.402	[−0.275, 0.755]	−0.157	0.322	[−0.566, 0.269]	0.134	0.344	[−0.579, 0.304]
Conscientiousness	−0.354	0.359	[−0.823, 0.085]	−0.364	0.341	[−0.779, 0.068]	−0.355	0.381	[−0.826, 0.108]
Extraversion *	0.547	0.402	[0.075, 1.055]	0.177	0.339	[−0.256, 0.619]	0.222	0.405	[−0.305, 0.728]
Not very often listen to the voice prompt and have people in car *	0.567	0.334	[0.129, 0.979]	0.524	0.325	[0.124, 0.937]	0.525	0.336	[0.107, 0.972]
Standard deviation of parameter							0.028	0.01	[0.016, 0.045]
Dissatisfaction with road infrastructure and condition *	0.333	0.235	[0.089, 0.678]	0.278	0.408	[−0.249, 0.820]	0.276	0.404	[−0.235, 0.822]
Dissatisfaction with actual work	0.299	0.310	[−0.101, 0.688]	0.269	0.301	[−0.121, 0.675]	0.296	0.293	[−0.076, 0.673]
constant	0.536	0.937	[−0.645, 1.758]	0.517	0.917	[−0.711, 1.648]	0.676	0.981	[−0.6, 2.002]
Random effect				0.499	0.061	[−0.681, 1.629]			
DIC		216.078			214.126			215.811	

* mesns significant variable at 90% level.

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