A Risky Driving Behavior Scoring Model for the Personalized Automobile Insurance Pricing

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ABSTRACT

Telematics [1] techniques enable insurers to capture the driving behavior of policyholders and correspondingly offer the personalized vehicle insurance rate, namely the usage-based insurance (UBI). A risky driving behavior scoring model for the personalized automobile insurance pricing was proposed based on telematics data. Firstly, three typical UBI pricing modes were analyzed. Drive behavior rate factors (DBRF) pricing mode was proposed based on mileage rate factors (MRF), in which insurance rate for each vehicle can be determined by the evaluation of individual driving behavior using OBD data. Then, on the basis of the analysis of influencing factors of safe driving, a driving behavior score model was established for DBRF by the improved EW-AHP (Entropy Weight- Analytic Hierarchy Process) Method. Finally, driving behavior scores of 100 drivers were computed by using the data collected from a 6-month field experiment. The results of three statistics analysis showed that the driving behavior score model could effectively reflect the risk level of driver's safe driving and provide a basis for the individual discount or surcharge that insurers offer to their policyholders.

CCS CONCEPTS

• **Human-centered computing → HCI theory, concepts and models;** Interaction design theory, concepts and paradigms;

KEYWORDS

Automobile Insurance, Driving Behavior Evaluation, EW-AHP Method, Usage Based Insurance

1 INTRODUCTION

Drivers play an important role in road traffic system who control the whole vehicle running process as the information handlers and decision-makers. Drivers' driving behavior affect the level of road traffic safety directly and is important to the stability of the whole traffic system.

At present, there is no uniform definition for driving behavior [1]. This paper holds that driving behavior is a complex process composed of various factors that influence driving behavior, indices of driving behavior and specific operation behaviors in different psychological conditions. The influence factors of driving behavior including objective factors including mileage, fatigue driving, drunk driving, illegal driving and gender, as well as subjective factors under various psychological state like lane-change, Overtaking, acceleration, turning.

At home and abroad, the research of driving behavior is mainly focused on driving behavior impact on traffic safety. Scholars put emphasis on the analysis of the relationship between driving behavior and traffic accidents as well as the evaluation of driving behavior. Intensive research demonstrate that the mileage, fatigue driving, alcohol use, hard deceleration, acceleration, swerve maneuvers, traffic violations and accidents are positively related to the traffic accidents and have a potential impact on traffic safety [2]-[6]. However, as far as the driving behavior evaluation, on the one hand, most of the studies provide support for road traffic safety by identifying unsafe driving behavior ,while a few of them discuss the driving behavior evaluation for rating of usage based insurance (UBI) [5][7]. On the other hand, the driving behavior data needed for driving behavior evaluation is mostly obtained by means of questionnaires such as DBQ questionnaire and its improved version applied widely [8]-[10].There are also some scholars obtain driving behavior data through GPS or driving recorder combined with sensors and a long time observation experiment to volunteers [5][11]. However, the subjectivity and one-sidedness of questionnaire often make research results cause error. At meanwhile, the GPS and the vehicle recording system are restricted because of privacy. In fact, On-board diagnosis (OBD) technology can effectively solve above problems. OBD can analyze the condition of vehicle energy consumption, breakdowns and the driver's habits after filtering private information such as driving trajectory during data uploading. Finally, only accurate data needed for the research is read.

Based on the driving behavior data obtained by OBD, a driving behavior scoring model of UBI is established for the individual rating of UBI. First of all, this paper defines the driving behavior evaluation purpose through the analysis of the UBI pricing model. Secondly, after analyzing the driving safe

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influence factors, this paper designs the evaluation indices system of driving behavior by using the improved Entropy Weight-Analytic Hierarchy Process (EW-AHP) to determine the index weight. Finally, the driving behavior scoring model for UBI is established and its validity is verified by field experiments.

2 UBI AND PRICING MODEL

UBI (Usage Based Insurance), which is based on the usage of insurance pricing model, the basic idea is that the premium should depend on the actual driving time, place, driving habits and driving behavior. The driver with safe driving behavior should get the premium discount. In this way, the human factor is taken into consideration so as to provide different services and premium.

In recent years, UBI has become a research hotspot abroad, and some insurance companies have also launched related UBI products, of which the United States, Britain and Germany insurance companies are more prominent. There are some companies which has applied driving behavior to personalized premium successfully, such as the Snapshot of Progressive and Drive Safe & amp of State Farm in America and MeinCopilot of Provinzial in German et al [12][13]. In domestic, the current UBI products are still in exploration period and immature in the market at present.

UBI mainly has three pricing models. (1) Per-mile premiums (PMP) model . The vehicle insurance is sold by the vehicle-mile rather than the vehicle-year. Other rating factors are incorporated, so higher-risk drivers pay more per mile than lower-risk vehicles. (2) GPS-Based Pricing. This system uses GPS transponders installed in vehicles to price insurance based on time and location. Motorists may choose to purchase insurance based on when and where they drive using a GPS transponder installed in their vehicles. (3) Mileage rate factors (MRF) model. Annual mileage is incorporated into the premiums as a rating factor. The insurers will offer some discounts to those drove low mileages, and surcharge to those traveled high mileages [4] [12].

Generally, MRF can be expanded to drive behavior rate factors (DBRF). Insurers offer discounts or surcharges (a rate adjustment coefficient) on the basis of the existing premium according to policyholders risky drive behavior performance, which can be reflected by some risky factors such as speed, region, mileage, the time of day, roadway types, hard deceleration, acceleration, swerve maneuvers etc. For DBRF model, the rate adjustment coefficients can be determined by a linkage model between the rate adjustment coefficients and the driving behavior score based on the evaluation of driving behavior. Firstly, the scores are determined by driving behaviors. Then discount rate is proposed for each score grade.

While the relationship of various driving behavior factors to the risk of accident has been discussed by many researchers, literature about individual rating of UBI based on driving behaviors is sparse. Many researchers discussed the influence of mileage, speed, and some temporal-spatial driving behavior activity such as time of day, roadway types, hard deceleration, acceleration, and swerve maneuvers on road accidents [1][3][4][14]-[26]..

As far as UBI Pricing be concerned, Ferreira [17] used the generalized linear model to compute pure premium per mile in which mileage is used in conjunction with those traditional rating factors. That study just considered mileage and ignored other drive behavior factors. Consequently, this study established a risky driving behavior scoring model for the UBI pricing based on more driving behavior factors including mileage, speed, time of day, hard deceleration, acceleration, and swerve maneuvers etc.

3 ANALYZING IMPACT FACTORS OF DRIVING SAFETY

There are many factors that influence driving behavior and safety. Some scholars have summed up the 53 influencing factors [27], and the number of influence factors are as many as 18 by expert scoring and questionnaire investigation [10]. For the purpose of this research, in this paper, 6 most typical impact factors including mileage, driving time, traffic flow, speeding, traffic violations, hard deceleration, acceleration, and swerve maneuvers were selected to analyze the impact to driving safety.

(1) Mileage

The relationship between the distance run by a vehicle and its influence on the risk of accident has been discussed by many researchers. Some of them have established correlations between mileage and insurance claims [17] as well as mileage and crash fatalities [4]. While the Texas Mileage Study published by Progressive Insurance found a linear relationship between mileage and insurance claims, the literature has also discussed non-linear relationships [18], particularly for low-mileage drivers[19][20]. In general, Vehicle mileage is positively related to driving risk. The greater the mileage traveled by the same vehicle during the insurance year, the greater the likelihood of an accident. In china, traffic accident loss can increase by 1% every increase of mileage 5.41% [28].

(2) Fatigue driving

Studies have shown that fatigue driving is one of the important reasons of traffic fatalities. Maclean’s statistics show that 20% of traffic accidents are related to fatigue driving [13]. A research report of DOT also has pointed out that the commercial vehicle accident 20% ~ 40% is due to fatigue driving. Through the analysis of 182 cause of heavy truck driver died accidents, it shows that 31% of accidents is related to driver fatigue [29]. In terms of reasons of fatigue driving, drivers in sleep-related crashes are more likely to work night shifts, drive more often late at night, driving for longer time [30]. Nighttime risk ranks at the top of the list for the youngest motorists on the road [26].

(3) Traffic flow

The magnitude of traffic flow directly influences the degree of mental tension and the rate of traffic accidents, which is one of the main factors that influence the number of traffic accidents.

Through long observation experiments, Martain finds that traffic flow is closely related to the traffic accident and the severity of the accident [29]. The experimental data show that the severity of traffic accidents has a direct relationship with the traffic flow [31].

(4) Speeding

Speeding has an impact on vehicle safety by affecting the driver's visual characteristics and vehicle stability. Davis found crash risk clearly tended to increase as speed increased [22]. Matthew's research points out that the degree of crash risk increases exponentially with the increase of driving speed [32]. Nilsson developed a power model of the relationship between speed and accidents [33]. Elvik evaluated above power model of the relationship between speed and accidents, and established a set of power functions [23].In the first quarter of 2014, there were road accidents occurred reaching 40283 in the country which had resulted in 10575 deaths and 210 million RMB of direct property losses. The number of accidents caused by high-speed driving accounted for 5.5% of the total [16].

(5) Traffic violations

Traffic violation is one of the main factors to induce road traffic accidents. According to statistics, traffic accidents caused by Traffic violation accounted for more than 50% of total number of accidents and more than 70% of causing casualties. In all traffic accidents involving junctions in 2014, 1895 people were killed and 8048 people were injured in 7415 road accidents. Among them, 1895 deaths and 5970 injured people occurred because of 4954 accidents in which the automobile broke traffic signals regulations [16].

(6) Hard deceleration, acceleration, and swerve maneuvers

Hard deceleration, acceleration, and swerve maneuvers means the sudden acceleration/ braking/ turning behavior. These behavior would affect the vehicle technical condition, so the vehicle is prone to occur security risks. A study carried out by the American Progress company shows that the driver's driving cost of high-risk driving behaviors with hard deceleration, acceleration, and swerve maneuvers is about 2.5 times than the low risk's [13]. Jun carried out an empirical investigation to determine if drivers with a crash experience have driven differently in terms of speed, time of day, and roadway types, hard deceleration. He found that crash-involved drivers had usually traveled longer mileage, normally traveled at higher speeds than non-crash drivers, and frequently engaged in hard deceleration events [24]. Klauer found that unsafe drivers turned their vehicles at greater than 0.30 g, decelerated greater than 0.30 g, and swerved greater than 3ft/s significantly more frequently than either the moderately safe or safe drivers [25].

4 DRIVING BEHAVIOR SCORING INDICES SYSTEM AND WEIGHT DETERMINATION

4.1 Establishing the indices system

The above 6 factors influencing driving safety based on driving behavior data can be collected by the combination of OBD. Based on the 6 factors influencing driving safety and the data from OBD, in this paper, 10 variables is selected as the evaluation indices including the monthly total mileage, peak time on weekday, night and weekend time, the time rate(80～120km/h, >120km/h), times of violations, hard deceleration, acceleration, and swerve maneuvers. The multi-level driving behavior evaluation indices system is set up based on these indices, as is shown in table 1.

TABLE1. BEHAVIOR EVALUATION INDICES SYSTEM

Target Level	First-Class	Second-Class	Variable Declaraion
driving behaviors scoring	mileage and time	monthly total mileage	continuous
		weekday peak time	continuous
		night driving time	continuous
		Weekend driving time	continuous
	speeding time rate	80～120km/h	continuous
		>120km/h	continuous
	different driving condition times	acceleration times	continuous
		hard deceleration times	continuous
		swerve maneuvers times	continuous
		violations times	continuous

4.2 Determining the weights

It's very important to reasonably determine the weight of each index in the progress of establishing the scoring model. In this paper, an improved EW-AHP method is used to calculate the weights of each index.

(1) Improved EW-AHP (Integrated weighting method)

The traditional EW-AHP is a simple combination to get weight of the bottom indices which is got through AHP and Entropy weight method. There will be an imbalance comprehensive weight because of greater difference of values obtained by the two methods. In order to avoid the above shortcomings, this paper adopts improved EW-AHP method which combines both intermediate calculation process to get the final weights of the indices. Not only the data itself of the method can be reflected, but also the method meets the actual application demands [34].

(2) The method of weight calculation based on EW-AHP

a. First of all, suppose that the number of upper level criterion and sub criterion are m and n. Each upper criterion consists of following variables: $n_1, n_2, \dots, n_m$. Through the Judgment Matrix of AHP method, the weights of upper level criteria and sub criteria are got respectively as $B = \{\beta_1, \beta_2, \dots, \beta_n\}$ & $= \{\gamma_1, \gamma_2, \dots, \gamma_n\}$.

b. Next, suppose that the weight of each index by EW as $A = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$.

c. Then, integrating the sub criteria weight D and EW A to get the comprehensive weights in sub criteria level as $\tau = (\tau_1, \tau_2, \dots, \tau_n)$, and

$$\tau_i = \frac{\alpha_i \gamma_i}{\sum_{i=1}^{n} \alpha_i \gamma_i} \quad (i=1,2\dots,n) \tag{1}$$

d. According the correspondence of sub criteria and upper criteria, the comprehensive weight is carried out again as $T = \{\tau_{11}, \tau_{12}, \dots, \tau_{1n_1}, \tau_{21}, \tau_{22}, \dots, \tau_{2n_2}, \tau_{m1}, \tau_{m2}, \dots, \tau_{mn_m}\}$. And Normalization Processing each sub level criterion and getting the weight as $\mu = \{w_{11}, w_{12}, \dots, w_{1n_1}, w_{21}, w_{22}, \dots, w_{2n_1}, w_{m1}, w_{m2}, \dots, w_{mn_n}\}$ and

$$w_{ij} = \frac{\tau_{ij}}{\sum_{i=1}^{n} \tau_{ij}} \tag{2}$$

(i=1, 2,…n; j=1, 2,…m; k=$n_1, n_2, \dots, n_m$)

e. Multiplying the weight B (upper level) and μ (corresponding comprehensive weight) to get the new weight as $\mu' = \{w_{11}', w_{12}', \dots, w_{1n_1}', w_{21}', w_{22}', \dots, w_{2n_1}',$
$w_{m1}', w_{m2}', \dots, w_{mn_n}'\}$, and

$$w_{ij}' = \beta_i w_{ij} \tag{3}$$

(i=1, 2,…, n; j=1,2,…, k; k∈ $(n_1, n_2, \dots, n_m)$)

f. Reformulating the μ' into $\mu' = \{w_1, w_2, \dots, w_n\}$ and normalizing processing to get $w = \{w_1, w_2, \dots, w_n\}$, and

$$w_i' = \frac{w_i'}{\sum_{i=1}^{n} w_i'} \tag{4}$$

(3) The results of weight

A Questionnaire on Importance of Driving Behavior Indices has been issued to experts in the transport filed and insurance companies to get the evaluation of the importance of each factor of driving behavior. On this basis, through formula (1) ~ (4), using AHP, EW and improved EW-AHP method to calculate the weight of each index, the results are shown in table 2.

TABLE2. THE WEIGHT OF DRIVING BEHAVIORS SCORING INDICES

Indices	AHP Weight	EW Weight	EW-AHP Weight	Scores
monthly total mileage μ_1	0.0273	0.1039	0.0765	8
weekday peak time μ_2	0.0162	0.076	0.0462	5
night driving time μ_3	0.0639	0.0682	0.1044	10
weekend driving time μ_4	0.0098	0.1459	0.0401	4
time rate (80～120 km/h) μ_5	0.1024	0.1207	0.1543	15
time rate (>120km/h) μ_6	0.512	0.1016	0.2601	26
acceleration times μ_7	0.0441	0.0879	0.0749	7
hard deceleration times μ_8	0.0282	0.0595	0.0381	4
swerve maneuvers times μ_9	0.0764	0.0913	0.0804	8
violations times μ_{10}	0.1196	0.1451	0.125	13
Total	1.0	1.0	1.0	100

Based on the weights calculated by the improved EW-AHP method, it is converted into a percentile system to obtain the scores of the second-class in the driving behavior scoring model.

5 BUILDING THE DRIVING BEHAVIOR EVALUATION INDICES SYSTEM

In order to apply the model in practice, on the basis of determining the indices and weights, we need to set a number of options for each index. The driver's score is evaluated according to the options, and the scores of the indices are accumulated as the final scores.

Determining the option and its value. Firstly, the sample data of each factor collected have been analyzed statistically. On the basis of last step and expert opinions, Alternative answers of driving behavior scoring model as well as scores are determined. The details are shown in Table3.

TABLE3. DRIVING BEHAVIORS SCORING MODEL

Scoring Indices	Scores	Options	Values
1.mileage and time	27	—	—
monthly total mileage	8	≤100 km	8
		[100, 500) km	7
		[500, 1000) km	5
		[1000, 1500) km	4
		[1500, 2000) km	3
		[2000, 2500) km	2
		≥2500km	1
weekday peak Time	5	≤5 h	5
		[5, 10) h	4
		[10, 20) h	3
		[20, 30) h	2
		≥30 h	1
night driving time	10	≤1 h	10
		[1, 2) h	9
		[2, 4) h	8
		[4, 6) h	7

		[6, 10) h	6
		[10, 15) h	5
		[15, 20) h	4
		[20, 25) h	3
		≥25 h	1
weekend driving time	4	[0, 5) h	4
		[5, 10) h	3
		[10, 15) h	2
		[15, 20) h	1
		≥20 h	0
2.speeding time rate	41	—	—
80～120 km/h	15	0	15
		(0, 0.5%)	14
		[0.5, 1%)	13
		[1%, 3%)	11
		[3%, 6%)	9
		[6%, 9%)	7
		[9%, 12%)	5
		[12%, 15%)	3
		≥15%	1
>120 km/h	26	0	26
		(0, 0.1%)	24
		[0.1%, 0.5%)	22
		[0.5%, 1%)	20
		[1%, 2%)	17
		[2%, 3%)	14
		[3%, 4%)	10
		[4%, 5%)	6
		≥5%	1
3.different driving condition times	32	—	—
acceleration times	7	0 times	7
		[1, 5)times	6
		[5, 10)times	5
		[10, 20)times	4
		[20, 30)times	3
		≥30 times	1
hard deceleration times	4	≤5 times	4
		[5, 10)times	3.5
		[10, 20)times	3
		[20, 35)times	2
		[35, 50)times	1
		≥50 times	0
swerve maneuvers times	8	0 times	8
		[1, 5)times	7
		[5, 10)times	6
		[10, 20)times	5
		[20, 30)times	4
		[30, 40)times	3
		[40, 50)times	2
		≥50 times	0
violations times	13	0 times	13
		1 times	10
		[2, 3)times	6
		[3, 5)times	2
		≥5 times	0

6 EXPERIMENT AND RESULT ANALYSIS

A traffic communication company with a property insurance company in Chongqing launch a UBI field experiment to promote the installation of OBD products and collect data of customers' driving behavior. From October 2014 to April 2015, 165 users of OBD have been installed. Through the integration of customer personal data and driving behavior data, removing abnormal and invalid data, they get driving behavior data from 100 customers. The driving behavior data of customers includes monthly total mileage, weekday peak driving time, night driving time, weekend travel time, speeding time ratio (80～120km/h, >120km/h), hard deceleration, acceleration, swerve maneuvers, and the number of violations.

(1)The results of driving behaviors scoring

Firstly, Import the customers' behavior data of 100 drivers into scoring model. Then, calculate scores of driving behavior of each customer. Finally, statistical analysis is done to accident cases during the experiment time in order to get a cross-reference table of driving behaviors scoring and history accident times, as is shown in table 4 (Only listing 4 highest scores and the 6 lowest score).

TABLE4. DRIVING BEHAVIORS SCORES AND ACCIDENT TIMES

Serial Number	Scores	Accident Time
1	91	0
2	73	1
3	37	1
4	68	0
…	…	…
95	72	0
96	85	0
97	87	0
98	63	2
99	60.5	0

100	88.5	0

(2)A correlational analysis between driving behaviors scoring and the numbers of history accidents.

Based on Table 4, a correlational analysis of Spearman is performed (Owning to the limitation of the scope, the table of analysis results will not show in this paper).

Based on the analysis results, the correlation coefficient between the score and the number of accidents is -0.504, which means a negative correlation. The unrelated bilateral significance was 0<0.01. So there was significant negative correlation between scores and accident times.

(3) A correlational analysis between driving behaviors scoring and history accidents

Carry out a subtotal from table 4 and get the result in table 5. (Mean accident times= Total accident times/ Number of people)

TABLE5. SUBTOTAL SCORES OF DRIVING BEHAVIORS

Scores	Number of People	Total Accident Times	Mean Accident Times
1(<40)	6	9	1.5
2(40～60)	10	10	1
3(60～70)	22	13	0.59
4(70～80)	33	7	0.21
5(80～90)	23	1	0.043
6(>90)	6	0	0

After the statistical analysis of the table 5, firstly, make y= Mean Accident Times and x=Scores. Then fit the relational model between them. The results are shown in Table 6 and figure 1.

TABLE6. THE FITTING RESULTS OF DRIVING BEHAVIORS SCORES AND MEAN ACCIDENT TIMES

Equation	Model Statistic					Parameter Estimation		
	R^2	F	df1	df2	Sig.	Constant	b1	b2
Liner	.927	51.114	1	4	.002	1.633	-.307	
Logarithm	.987	292.499	1	4	.000	1.538	-.894	
Quadratic	.998	693.415	2	3	.000	2.173	-.713	.058

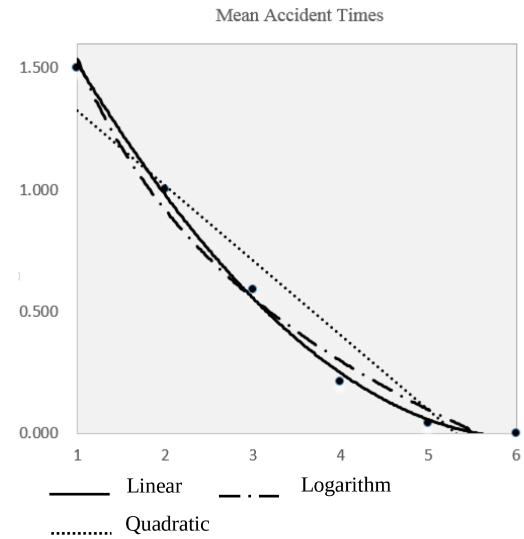

FIGURE 1. THE FITTING GRAPH OF DRIVING BEHAVIORS SCORES AND MEAN ACCIDENT TIMES

From table 6 and figure 1, the best fitting function is quadratic function model (R2=0.998), followed by Logarithm model. From the F value, the best fitting is quadratic function (F = 693.415). The sig. value of the logarithm model and the quadratic model is 0, which shows that the model is more significant and has better predictive capability.

Here is the quadratic model between mean accident times and driving scores.

$$y = 2.713 - 0.713x + 0.058x^2 \qquad (5)$$

Through the correlational analysis and model fitting, there is a significant correlation between the score and accident times, the higher the driving score is, the less the accident times. Therefore, the model can effectively reflect the driver's risk level of driving safety and has a great significance in practice.

7 CONCLUSION

UBI model is the trend of automobile insurance rates at home and abroad. In the DHRF pricing model, driver behavior evaluation is essential for the individual insurance rating for automobile. First of all, by analyzing the UBI pricing model, this paper points out the importance of driving behavior evaluation. Next, based on the analysis of the driving safety factors, the driving behavior evaluation indices system is designed. After the indices weights are determined by the improved EW-AHP method, a DBRF of UBI is established. Finally, the OBD driving behavior data of 100 customers is collected through field experiments. The score of each customer is calculated by scoring model and a statistical analysis is conducted. Final result shows that the DBRF can provide a basis for individual insurance rate so as to improve automobile insurance pricing model and to optimize the rate structure. At meanwhile, this will help to enrich insurance pricing theories of Internet of Vehicles.

Of course, because of the small amount of sample data, some missing data and only keeping claim times not claim amount, the discount rates of different driving behaviors scores can't be calculated directly. However, with the expansion of OBD applications, driving behavior data can be collected in a large-scale. Combined with the database of automobile insurance records, the linkage model of insurance rates and driving behavior scoring will be constructed to determine the discount rates for different driving behavior scores so as to realize the automobile insurance rating based on UBI.

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