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Review

A Comprehensive Review of Driving Style Evaluation Approaches and Product Designs Applied to Vehicle Usage-Based Insurance

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Abstract: Vehicle insurance is a very important source of income for insurance companies, and it is closely related to the driving style performed by driving behavior. Different driving styles can better reflect the driving risk than the number of violations, claims, and other static statistic data. Subdivide the vehicle insurance market according to the personal characteristics and driving habits of the insured vehicles, and studying the personalized vehicle insurance products, will help the insurance companies to improve their income, help the drivers to change their bad driving habits, and thus help to realize the healthy development of the vehicle insurance industry. In the past 20 to 30 years, more and more insurance companies around the world have launched vehicle usage-based insurance (UBI) products based on driving style analysis. However, up to now, there are few comprehensive reports on commercial vehicle UBI products and their core driving risk assessment methods. On the basis of literature indexing on the Web of Science and other academic platforms by using the keywords involved in vehicle UBI, over 100 relevant works of literature were screened in this paper, and a detailed and comprehensive discussion on the driving style evaluation methods and the design of commercial vehicle UBI products during the past 20 to 30 years has been made, hoping to get a full understanding of the possible factors affecting driving style and the collectible data that can reflect these factors, and to get a full grasp of the developing status, challenges and future trends in vehicle insurance branch of the Internet of Vehicles (IoV) industry.

Keywords: vehicle insurance; usage-based insurance (UBI); driving style; driving behavior; driving risk evaluation

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1. Introduction

It is of no doubt that vehicle usage-based insurance (UBI) is competitive in the commercial vehicle insurance market. Vehicle UBI, as its name suggests, is a type of vehicle insurance, in which the premium is adjusted and determined via specific vehicle usage behavior and its corresponding risk level. The insurance company that carries out vehicle UBI products usually extracts the corresponding risk type parameter for different driving behaviors and habits of insured vehicles during their underwriting cycle by means of data collection, adjusts the premium accordingly on the basis of the premium of traditional commercial vehicle insurance in the next cycle, and finally determines the differentiated premium for the insured vehicles. Till now, there are still no clear standards for the differentiated premium adjusting mechanism of vehicle UBI products, which can judge the risk type only for a certain type of driving parameter (such as driving mileage [1], or driving speed [2]), or the comprehensive risk type for multiple driving parameters [3].

At present, in the risk judgment of vehicle UBI based on single driving parameters, the common evaluation mechanisms are pay-as-you-drive (PAYD) [1,4] and pay-as-you-speed

(PAYS) [2]. PAYD mechanism takes mileage parameters as the basis for risk judgment, its extreme situation is “there is no risk if you don’t drive”. PAYD mechanism believes that the more mileage an insured vehicle drives in the underwriting cycle, the greater the probability of risk it faces. Similarly, the PAYS mechanism takes the speed parameter as the basis for risk judgment, its extreme situation is “there is no risk if you don’t exceed the speed limit”. PAYS mechanism believes that the more times an insured vehicle exceeds the speed limit on roads in the underwriting cycle, the greater the probability of risk it faces. The determination of risk parameters of PAYS is more complex than that of PAYD. It needs the support of vehicle positioning technology to determine whether the vehicle has overspeed behavior on a specific road.

In terms of risk judgment for vehicle UBI based on multiple driving parameters, the most common concept is pay-how-you-drive (PHYD) [4]. PHYD is a risk assessment mechanism for insured vehicles that comprehensively considers multiple driving parameters, including time duration, road section, real-time speed, real-time acceleration, mileage, and so on in each period of driving. The biggest difference between PHYD and PAYD and PAYS is that the risk assessment of insured vehicles is carried out dynamically, and the corresponding risk assessment parameters can be changed every time the vehicle is driven, rather than making regular later static analysis on the driving mileage or overspeed times in a specific period of insurance cycle [5].

On the basis of literature indexing on the Web of Science and other academic platforms by using the keywords involved in vehicle UBI, in this paper, over 100 relevant pieces of literature were screened to make a comprehensive review on not only driving style evaluation issues, but product design as well. In this section, the background of vehicle UBI products and their related concepts have been given, the remainder of this paper is organized as follows: the types and advantages of commercial vehicle UBI products are discussed in Section 2. Then in Section 3, a detailed and comprehensive discussion on both micro and macro driving style evaluation methods is made. In Section 4, the design of commercial vehicle UBI products during the past 20 to 30 years is made. Finally, the conclusion and comments are drawn in Section 5.

2. Vehicle UBI and Its Advantages

2.1. Overview of Commercial Vehicle UBI Products

In Europe and America, commercial vehicle UBI products have been already implemented for 20~30 years. The implementation strategies of commercial vehicle UBI products are different, and the premium determination method can also be described as “a hundred schools of thought”. From the different vehicle UBI products, it can also be found that there is no unified standard for the driving risk assessment of vehicle UBI products, and the implementation of products can be regarded as moving forward in exploration. Of course, it must also be pointed out that not all European countries have carried out vehicle UBI products very smoothly. There are also some countries whose nationals are relatively conservative in sharing travel trajectories and do not accept such forms of insurance products with driving data collection during the underwriting cycle as the mean of premium adjustment and determination [6].

Progressive, an insurance company in the United States, launched its first generation of vehicle UBI product Autograph as early as 1998. The product uses global positioning system (GPS) for data collection of driving behavior, but the specific pricing mechanism is not disclosed. Later, Progressive has launched its second-generation UBI product Tripsense. In 2008, its third-generation UBI product Myrate came out, which technically did not use GPS to collect data from insured vehicles and pays more attention to the protection of user privacy. In specific operations, Myrate only collects driving time and mileage information through an onboard data transceiver module [7]. In addition to Progressive insurance, General Motors also embedded auto financial services in its product OnStar since the year 2004 and provided PAYD auto insurance services [8]. The vehicle UBI product was launched by Norwich Union Insurance Company in the UK in 2006. The product adopts a more radical strategy in its commercial implementation mode, that is, for those insured vehicles with low driving risk, it gave an ultra-low rate of 1 penny per mile [6]. However, the implementation strategy of Norwich Union was not highly recognized, and its vehicle UBI products were forced to go offline two years later. The mainstream vehicle UBI products in the UK were later replaced by products launched by another company called Coverbox [9].

Other European countries have also launched some representative vehicle UBI products. Octo Telematics in Italy has established its own ICT system for the vehicle UBI products, which can dynamically analyze the driving behavior of drivers, and has successfully promoted over 800,000 users. Octo Telematics has established an average speed file with a resolution of 15 min for main roads, which can be effectively utilized for government traffic guidance and management [10]. The representative vehicle UBI product in Belgium and Netherlands is Polis Direct, which has a linear premium policy in driving kilometers [11]. In addition, Denmark is also one of the countries which have successfully implemented PAYD and PAYS products. To be specific, PAYD in Denmark can provide a discount of up to 30% of the premium; in addition, PAYS in Denmark can help effectively restrain overspeed behavior on various speed-limited roads [2].

2.2. The Advantages of Commercial Vehicle UBI Products

For policyholders, the biggest advantage of promoting vehicle UBI products lies in the mechanism of calculating differentiated premiums based on the risk type of insured vehicles and their corresponding drivers. Such a mechanism has taken more comprehensive factors related to driving risk into consideration, so that low-risk and cautious drivers can obtain the benefits from a premium policy, and their cross-subsidy to high-risk policyholders can be effectively avoided. For insurance companies, the advantage of promoting vehicle UBI products can better help the underwriting process, which means that insurance companies can not only accurately grasp the first-hand data of policyholders, but also fully grasp their driving habits.

Vehicle UBI products has been launched around the mid-1990s in developed countries, and the most common form of UBI products in its early developing stage was PAYD. PAYD products also developed rapidly in Europe at the beginning of the 21st century [12]. In the academic field, with the obvious achievements of PAYD products in the vehicle insurance industry in developed countries, the reports on the advantages of vehicle UBI products are gradually increasing. Greenberg has discussed the generation motivation, implementation mechanism, and advantages of PAYD products [13].

In addition to the fairer premium calculation and the regulatory effect on driving, vehicle UBI products also have some other hidden advantages. As mentioned above, the PAYD product pays attention to the risk corresponding to driving mileage, so then it can on some level restrict unnecessary travel to a certain extent, and can thus play a positive role in reducing accidents. Edlin et al. have analyzed the external impact of traffic accidents and demonstrated the role of policy means (including policies on vehicle UBI products implementation) in promoting traffic safety [14]. Parry and Litman have successfully demonstrated the positive role of PAYD products in reducing urban traffic accidents [4,15]. Bolderdijk et al. have demonstrated that the premium paid for driving significantly reduced the speed violations of young drivers by setting up a control group [16]. Dijksterhuis et al. have pointed out that vehicle UBI products can not only enable policyholders to improve product participation through the instant feedback provided by the interface of the on-board modules provided by the products, but also enable them to be guided to adopt safer driving styles [17], as shown in Figure 1.

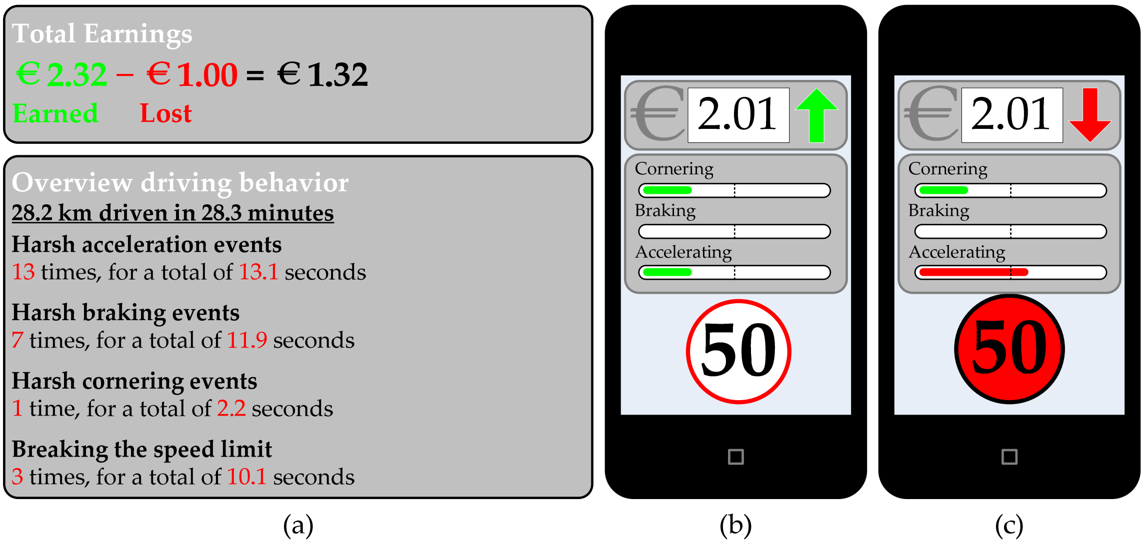

Figure 1. Different feedbacks of the onboard system provided by UBI products: (**a**) short message prompts; (**b**) reward prompts; (**c**) punitive prompts [17].

Apart from traffic accidents, fuel consumption and emissions of vehicles are closely related to their usage. Tselentis et al. have pointed out that drivers who use PAYD and PHYD products must pay a premium according to their exposure to public roads, such an economic mechanism can help to reduce traffic congestion and pollution emissions, and thus help to promote environmental protection [5].

3. Core Driving Style Analysis Method of Vehicle UBI

Vehicle UBI will of no doubt go through a very complex process of research, pilot, demonstration, and optimization before it is finally presented to users as a product. Among them, the driving style evaluation algorithm used to identify driving risks is the core of vehicle UBI products. The data collected for vehicle UBI products is a direct reflection of micro-driving behavior, and the analysis of micro-driving behavior can finally form a macro driving style classification.

3.1. Research on Differentiated Micro Driving Style

3.1.1. Driving Style Influenced by Cultural Environment

As mentioned above, the macro driving style is composed of micro driving behavior, and driving behavior is affected by many factors, among which the cultural environment factor is a very important aspect. The cultural environment factor includes driving environment and driver, and these two aspects will be discussed here in this section in detail.

1. Driving environment

Driving behavior may be affected by the driving environment. Doshi et al. have pointed out that different geographical conditions and congestion may change the driving habits of each driver to a great extent [18]. Schorr et al. have demonstrated that road infrastructure has a certain impact on the safety of driver behavior by collecting necessary data [19]. Wang et al. have also demonstrated that the change in driver's behavior depends largely on road characteristics by quantifying various parameters of driver's behavior on different road categories, including relative speed, leading speed, accelerator release, brake activation parameters, and so on [20]. Li et al. have proposed that the three-axis angular velocity, acceleration, vehicle speed, and other parameters in the low-cost inertial measurement unit (IMU) can be used to solve the road slope grade by estimating the vehicle pitch angle, so as to realize the high-precision identification of the geographical environment of different driving roads [21]. For road congestion, Nai et al. have established an optimized road congestion classification method, which is expected to be used as an environmental reference in the premium actuarial process of PHYD commercial vehicle insurance products to correct the real risk level corresponding to the assessed driving style [22]. In the past year, more scholars have noticed that the road environment may have a great impact on driving and tried to test driving behavior by simulating different driving scenarios through the latest virtual reality (VR) technology. Shi et al. pointed out through the analysis of the driving behavior of the participants in the virtual driving scene that the geometric characteristics of the road and environmental elements will have varying degrees of impact on the driver's emotion and behavior [23]; while Goedicke et al. have tried to realize the computer-driven vehicle from the interaction between driving environment and driving behavior [24].

The condition of the road surface is also one of the influencing factors of driving behavior. Dixit et al. have established a traffic two-fluid model to evaluate the traffic capacity of cities in different environments of dry and wet roads, at the same time, they have found that drivers are more conservative when the roads are wet, which can also be used as an index to evaluate safe driving [25]. By collecting real vehicle driving data, Weng et al. have studied different driving behavior modes of drivers under different road environments of asphalt, concrete, grassland, and gravel routes, and tried to accurately classify the road surface conditions through driving behavior data analysis [26].

The driving behavior of surrounding vehicles on the road will also affect the driving behavior. Chu et al., Guerrier et al., Okuda et al., and Gao et al. have all discussed the impact of merging or cut-in behavior from the ramp on the driving behavior of vehicles on highway or city main roads and have pointed out that there are significant differences in the behavior of different drivers towards the vehicles merging or cut-in, which may cause different levels of risk [27–30]. Ma et al. have collected data through video and questionnaire and have analyzed the impact of surrounding vehicle density on the lane changing frequency of the target vehicle by using mathematical statistics, their results have shown that there is a strong correlation between the two [31]. Wang et al. have introduced the driving mode of surrounding vehicles into the driving risk assessment model of the target vehicle, and have fully considered the speed, rapid acceleration, and deceleration of surrounding vehicles, as well as the relative relationship between the driving mode of surrounding vehicles and the driving mode of the target vehicle, and have employed convolutional neural network (CNN) combined with long-short term memory (LSTM) to analyze the characteristics hidden in multi-vehicle data [32].

2. Driver

As mentioned above, the driver may be affected by multiple factors, among which the influence of cultural factors in the local area cannot be ignored. Parker et al. and Lajunen et al. have proved that social culture has an impact on the driving behavior of people in specific areas, and vehicle insurance should be differentiated in terms of premium [33,34]; Xie et al. have also proved that regional differences also have a significant impact on peoples' driving styles [35].

The age and gender differences of drivers will also have a significant impact on driving behavior. Ozkan et al. have reviewed the impact of age and gender on driving behavior [36]. In terms of age-influencing factors, Laapotti et al. have pointed out that young men and women do have a higher tendency to overspeed [37]. Donmez et al. have conducted a driving simulator, which has studied 53 young drivers aged from 18 to 21, and have demonstrated that young drivers have a higher tendency to distract from driving tasks [38]. Freund et al. have pointed out that the elderly have more stable driving behavior [39]. In terms of gender influencing factors, Lyu et al. have pointed out that compared with female drivers, male drivers prefer to drive at high speed in the deceleration lane and take more severe braking measures [40].

The personality of the driver will also significantly affect driving behavior. West et al. has summarized the personality of seizing time, being competitive and vigilant, and being ambitious as type-A personality, and have studied the driving behavior habits of people with such personality, and the dialectical relationship between abnormal conditions such as social panic and speeding has been also demonstrated [41]; Garrity et al. have pointed out that personality and emotion have an impact on driving behavior [42]. Lajunen et al. have discussed the relationship between radical style and radical driving [43].

Driving behavior, as a reflection of driving habit, is not formed in a short time, and is closely related to the growth environment of drivers. Hartos et al. and Beck et al. have pointed out that parents have a certain impact on their children's driving risk [44,45]; Bianchi et al. have proved that driving is affected by both living environment and parents [46]; McKay et al. have made an empirical analysis on the influence of parents on their children's driving habits [47]; while Shope et al. have especially pointed out that in terms of high-risk driving habits, children have a stronger inheritance from their parents [48].

It must be admitted that the emotional state and psychological pressure of the driver are also factors that cannot be ignored that affect the driving behavior in a specific driving process. Westerman et al. have specifically analyzed the potential relationship between psychological fluctuation and illegal driving in the face of pressure and deviation from the correct driving path [49]. Lanata et al. have used the changes in the autonomic nervous system (ANS) to study the effects of heart rate variability, respiratory activity, and skin electrical response caused by emotion on the time response of the driver's steering wheel angle correction [50]. Yang et al. have considered the behavioral differences between drivers of different genders when driving with a high mental load and have discussed the impact of mental load on driving behavior through auditory tests [51]. Danaf et al. have studied some aggressive driving behaviors including repeated lane changes that may be caused by time pressure, congestion, and accidental delay [52]. Magnana et al. have analyzed the impact of high-pressure events (such as self-fatigue, traffic congestion, and poor visibility) on drivers' driving behavior [53]. Kim et al. have compared the characteristics of engine speed, vehicle speed, lane change, and turning reflected in the driving behavior of "normal" and "overload" drivers, and have pointed out that "overload" drivers are prone to perform danger behavior [54]. Requardt et al. have conducted experiments on normal drivers, trying to explain the driving state of depression, anxiety, and positive and neutral emotions in different driving styles [55]. Wang et al. have established a driver intention recognition model considering the emotional factors of drivers by collecting real driving and simulation experimental data and have realized the accurate prediction of emotional drivers' intention [56].

The decrease in visual visibility caused by climatic conditions will also affect the drivers' driving behavior. One of the factors that cannot be ignored that affects the driver's visual perception ability is fatigue, Grabarek et al. have pointed out that fatigue will reduce the driver's physical and mental efficiency, reduce the visual perception ability, and then cause accidents. [57]. Wang et al. have pointed out that under the condition of insufficient visual feedback, the driving performance of drivers will decline to varying degrees [58]. Roche et al. have demonstrated the impact of different visibility on driving operation with the help of some visual and tactile feedback parameters of drivers in the actual driving environment [59].

Vehicle performance also has an impact on driving behavior to a certain extent. Horswill et al. have studied the impact of vehicle brands on driving behavior and believed that expensive vehicles with more luxurious and good safety performance are more likely to breed relatively dangerous driving operations [60]. Colombaroni et al. have pointed out that different components of vehicle infrastructure will lead to different behaviors of drivers on roads with different types of traffic and geometric shapes, which will bring different potential risks [61].

The influence of cultural environment on driving style discussed in this part can be summarized in Table 1. It can be seen that the driving environment includes not only the surrounding geographical environment where the vehicle is located (such as road terrain, road conditions, road visual effects, etc.), but also the road environment where the vehicle is driving (such as the degree of congestion and the driving behavior of surrounding vehicles, etc.); the driver's influence on driving behavior includes the regional differences of the driver, as well as the driver's age, gender, personality, growth environment, psychological state during driving, etc.

Table 1. Research on the influence of cultural environment on driving style.

Research Objects	Main Influence Factors	Detailed Factors	Literatures
Driving style influenced by cultural environment	Driving environment	Geographical conditions	[18–21]
		Congestion	[22]
		Road visual effects	[23,24]
		Road surface conditions	[25,26]
		Behavior of surrounding vehicles	[27–32]
	Driver	Cultural Factors	[33–35]
		Age and gender differences	[36–40]
		Personality of driver	[41–43]
		Growth environment of driver	[44–48]
		Emotional state and psychological pressure of driver	[49–56]
		Decrease of visual visibility	[57–59]
		Vehicle performance	[60,61]

3.1.2. Driving Style Reflected by Collectable Data

With the continuous progress of information and communication technology, almost all kinds of sensors configured nowadays in the car have a stronger ability in driving data acquisition. At the same time, the acquisition of driving data no longer depends only on the vehicle itself, smartphones, in recent years, have also become an important way to obtain driving data. In addition, the fineness of the obtained driving data from various sources has also been greatly improved, which provides a greater possibility for quantitative evaluation of driving intention and accurate judgment of driving risk by employing big data analysis and artificial intelligence (AI) algorithms [62]. However, there is not so much research on data-based differentiated micro driving style analysis, which involves refining driving risks and developing vehicle UBI products.

As mentioned above, smartphones, as a carrier for driving data collection and driving behavior analysis, have been discussed by more and more scholars in recent years. Hu et al. have tried to identify driving risk factors in different environments through smartphones, by combining with geographic network information and dynamic traffic data [63]; Bejani et al. have tried to extract the necessary features in the driving process, classify driving style and apply it to driving risk assessment with the help of multi-sensors in smartphones and CNN algorithms [64].

At present, the research on driving style based on available data is mostly seen in the research on realizing low energy consumption or high ride comfort. Martinez et al. have summarized that driving style has an important impact on vehicle energy management and driving safety [65]. Barabino et al. have made a horizontal comparison of the subjective test of driving style and acceleration parameters collected based on Intelligent Transportation System (ITS) tools, trying to establish a comfort measurement table to provide reference suggestions for higher ride comfort [66]. Mata-Carballeira et al. have conducted an in-depth analysis of driving data of 20 drivers of different age groups and driving experience levels, and have assessed the driving characteristics, so as to give references for the development of autonomous vehicle driving from the perspective of both ecological driving and ride comfort [67].

There is a lot of research on driving style based on available data aimed at realizing safe driving. Wang et al. have effectively analyzed the driving safety of vehicle following behavior based on natural driving data and considering the heterogeneity, scarcity, and diversity of traffic accidents [68]. Liu et al. have also studied the safety of car-following behavior, analyzed the speed and acceleration data sets recorded by the navigation system using the actual road data sets in China and Switzerland, and have tried to find out the safety indicators that can reflect driving and car-following behavior [69]. Cheng et al. have proposed a vehicle behavior safety assessment method based on the improved Dempster-Shafer (D-S) evidence theory through the analysis of vehicle collision accident data, which realizes the perception of driving environment and driving state and provides a characteristic basis for the safety assessment of driving behavior [70]. Yin et al. have proposed a new driving risk estimation method for processing multi-source driving data, by considering the vehicle and road-related information at the same time, the risk level of behavior at each driving time section can be divided, and their method has been proved to be superior to many machine learning methods [71]. Liu et al. have found that most drivers only decelerate significantly before approaching the stop sign, and brake and stop at a short distance, therefore, they have proposed a set of acceleration/deceleration (A/D) time ratio and A/D distance ratio indices to describe the risk level caused by different braking style [72].

Driving style analysis based on collectible data accounts for a large proportion of the analysis on driving micro intention. Llorca et al. have developed an unsupervised pattern recognition framework, based on the unlabeled data obtained by smartphone sensors, the self-organizing mapping, deep self-encoder, and partition clustering algorithm in the framework are used to identify overtaking behaviors with different intentions [73]. Xu et al. have established a multi-layer perception (MLP) neural network (NN) based on real vehicle test data to establish a model for four types of mild aggressive driving behaviors on the highway, so as to provide a driving style closer to manual driving for unmanned driving [74]. Fugiglando et al. have also used unsupervised learning technology to learn a bunch of parameters such as brake pedal pressure, steering wheel angle, steering wheel momentum, engine speed, vehicle speed, and acceleration, to realize the effective classification of micro driving intention [75]. Christopoulos et al. have proposed an overspeed intention recognition method based on a deep neural network (DNN) structure, based on the automatic learning function of different types of road speeds collected by smartphones [76]. Cheng et al. have established a driving simulator and have conducted a variety of classification studies on the intention of car-following behavior of drivers in China and Germany [77]. Chen et al. have designed a robust H_∞ output feedback controller to track and discuss the change of steering style of specific drivers in the left turn lane in their early and later stages [78].

As mentioned at the beginning of this section, although there are many pieces of research on quantitative analysis of micro driving behavior based on data, there are few reports on driving behavior analysis to design vehicle UBI products. To establish the risk evaluation of different driving operations and apply it to PHYD commercial vehicle insurance, Zheng et al. have proposed a set of risk evaluation index systems of driving style in plain cities and have verified the objectivity and effectiveness of the proposed dynamic driving evaluation index system through the analysis of real vehicle driving examples [79]. Subsequently, Nai et al. have designed an effective visualization method for various indicators applied to driving risk assessment established in the previous study by using a hexagonal eye diagram, to provide timely tips for drivers and standardize the behavior of policyholders when UBI products are commercially available [80]. Chen et al. have compared the driving behaviors extracted from the video surveillance system based on the multi-objective particle swarm optimization (MOPSO) method and gave the driving risk level classification of specific driving actions from “safe” to “very risky” [81].

Some studies on micro-driving-style analysis may not be applied to vehicle UBI products, but at least for the purpose of evaluating the corresponding driving behavior risk, which can provide some references for the design of vehicle UBI products. Yan et al. have applied a Bayesian network (BN) to extract five main factors forming significant driving risk from a variety of basic driving parameters: driver status, gender, experience, vehicle status, and environment [82]. Han et al. have also focused on multiple driving parameters including vehicle speed, throttle opening, braking force, acceleration, vehicle position, steering angle, and yaw angle, and have tried to use the method of combining fuzzy logic and full Bayesian theory to evaluate the probability value of whether there is risk in specific driving behavior [83]. He et al. used relative spatial reconstruction (PSR) and CNN to classify the input driving data, so as to effectively characterize different driving styles of various risk modes such as normal driving, drunk driving, driving when using mobile phones, and reckless driving [84]. Liao et al. have constructed an analytic hierarchy process (AHP) model to rate the severity of multiple abnormal driving behaviors with different priorities and to effectively classify the risk level of drivers [85].

The relevant research on driving style based on collectible data discussed in this section can be summarized in Table 2.

Table 2. Studies on driving style based on collectible data.

Literature	Research Objects	Algorithms or Methodologies
[63]	Use smartphone data to realize driving feature recognition and risk assessment in different environments	Collaborative perception of geographic data and road condition data
[64]		CNN
[65]	Use the available data to evaluate the driving style in terms of energy consumption and comfort	Review
[66]		Integration of subjective and objective driving comfort evaluation
[67]		Self-organizing map-based data analysis
[68]	Use available data to identify dangerous driving behavior of vehicles	Car following behavior modeling
[69]		Extract safety indicators from driving speed and acceleration data
[70]		D-S evidence theory
[71]		Hazard classification of time-sharing driving action
[72]		A/D time ratio and A/D distance ratio analysis
[73]	Micro driving intention recognition using available data	Unsupervised learning
[74]		MLP-NN
[75]		Unsupervised learning
[76]		DNN, wavelet algorithm
[77]		Driving simulator design
[78]		H_∞ output feedback
[79]	Research for the purpose of designing insurance products or at least evaluating the risk of different driving styles	Establishment of risk evaluation index system
[80]		Visualization of risk assessment indicators
[81]		MOPSO
[82]		BN
[83]		Fuzzy logic and total Bayesian theory
[84]		CNN and PSR
[85]		AHP

It can be seen that the emergence of smartphones makes it possible for driving data to be accurately collected. The fusion of multi-source data can bring a more reliable basis for the description of driving style. Driving data with higher resolution can be applied not only to the judgment of micro driving intention, but also to the quantitative calibration of micro driving style including but not limited to vehicle UBI products. However, data-based driving style analysis has still not been used in vehicle UBI products quite much, which can also reflect commercial vehicle insurance still take a very cautious attitude in the methodology of identifying the risk levels of different micro driving styles.

3.2. Research on Differentiated Macro Driving Style

Differentiated macro driving style is a macro manifestation of micro behavior. It is also an index that actuaries pay the most attention to and requires the most detailed design in the process of vehicle UBI product design. It directly determines the objectivity of the risk evaluation of a specific policyholder. Of course, it also directly determines the premium.

In terms of the classification of macro driving style, French et al. have proved that factors affecting micro driving behavior such as age, gender, and personality will also be reflected in the macro style; in addition, driving mileage also has a certain impact on the formation of style [86]. In the classification of styles, different conclusions may be drawn due to different research methods. The representative of simple classification can be seen in the research of Johnson et al., which just divides driving styles into 2 types—"radical" and "non-radical" [87]; Tricot et al. also believe that driving styles can be simply divided into 3 categories: peaceful type, radical type and ordinary type [88]; Qi et al. believe that driving status plays a role in the connection between driving behavior and its corresponding style, and have divided driving status into 3 categories: "aggressive", "cautious" and "moderate" from the data collected by onboard detection sensors [89]; likewise, Yang et al. have also divided driving safety levels into "normal" driving, "low-risk" driving and "high-risk" driving, and analyzed the effectiveness of several different clustering algorithms in dividing driving behavior risk levels under different traffic flow and driver distraction scenarios [90]. Based on the analysis of a large number of survey data, Taubman-Ben-Ari et al. have divided driving style into 8 types: free type, anxiety type, adventure type, anger type, high-speed type, danger aversion type, caution type, and patience type [91]. Wang et al. have referred to the complex influence factors during driving as driving primitives and have designed a probability framework based on driving primitives, which can quantitatively measure the similarity of human driving behavior and form the clustering of driving types [92].

Based on the classification of macro driving styles, some scholars have also made detailed research on identifying specific driving styles or classification methodologies of driving styles. For identifying specific driving style, Boyce et al. have summarized the similar characteristics of radical drivers and have pointed out that young drivers often have a radical style and are prone to speeding violations [93]; Musselwhite have also made a detailed classification for radical drivers. They have combined driving with the environment and given four sub-dimensions: unintentional adventure, environmental feedback adventure, computational adventure, and continuous adventure [94]; Cura et al. have developed NN models based on LSTM and CNN respectively, focusing on acceleration, deceleration, and lane change behavior, and have conducted more detailed style analysis on aggressive bus drivers [95]; Gatteschi et al. have conducted a further subdivision study on the aggressiveness of driving behavior to non-motor vehicles [96]. For classification methodologies of driving styles, Abdelrahman et al. have proposed a framework for calculating driver risk status judgment based on baseline driving events and risk probability prediction, and have realized effective prediction of driving risk level with the help of machine learning (ML) model [97]; also based on ML algorithms, Yuksel et al. have proposed a high-precision and low-cost driver risk assessment black box system based on the driving data that can be obtained from accelerometers and gyroscope sensors and have specifically pointed out that the system can be used in vehicle UBI products [98].

At the beginning of this section, it has been mentioned that the different risk coefficients reflected in driving style are the core of the premium determination of vehicle UBI products, and the driving style evaluation is usually obtained by quantifying and refining the micro behavior represented by the original driving data using specific clustering analysis methods. However, just as micro driving behavior analysis, the research on refining macro driving style is also mostly based on road condition analysis and energy consumption calculation. Huang et al. have used 11 basic driving parameters to evaluate driving style and identify road conditions and congestion [99]. In the research on the core method of driving style evaluation for energy consumption calculation, Ericsson used 62 basic driving parameters to determine the driving style and studied the relationship between specific driving styles and energy consumption [100]. Langari et al. and Jeon et al. have reduced the driving style evaluation parameters used for energy consumption analysis to 31 and 24 respectively [101,102]; Lin et al. have used only 2 driving evaluation parameters for energy consumption style recognition [103]. As for calculation methods, Lin et al. and Johannesson et al. have used acceleration and speed parameters to establish style evaluation state vector and homogeneous Markov model respectively and used these models in driving energy consumption style judgment and prediction [104,105]. In their patent, Tanoue et al. have focused on refining the collected basic driving data such as speed and mileage and used the concerned energy efficiency to evaluate whether the driving style is energy-saving [106].

The very research on mapping the macro driving style classification into vehicle UBI products and thus forming a new dimension to determine the driving risk of policyholders are still really hard to be found at present because it on some level involves commercial secrets, but there are also some sporadic research reports. Cripe has provided a driving style evaluation method of non-real-time collection of driving mileage data based on the PAYD concept, such a method has tried to find the corresponding relationship between specific mileage and risk coefficient [107]. Based on driving cases, Walcott Bryant et al. have studied the driving behavior of policyholders and have created a new risk assessment method for different driving styles based on the traditional premium determination model of insurance products [108]. Wang et al. have especially pointed out that it is difficult to find an effective method to explain the deep correlation between driving style and its corresponding quantitative risk value and have tried to propose a driving risk assessment method based on fuzzy multi-criteria decision-making (MCDM) suitable for PHYD vehicle insurance premium actuary and have verified the effectiveness and reliability of this method through examples [109]. Only during the past year or two have the scholars tried to employ specific driving parameters to analyze the risk of different driving styles with the help of clustering algorithms based on AI algorithms, Zhang et al. and Sun et al. have used 3 key parameters related to speed and 2 key parameters related to vehicle interval respectively to effectively realize driving style clustering and to distinguish aggressive drivers and non-aggressive drivers [110,111].

The relevant research on differentiated macro driving styles discussed in this part can be summarized in Table 3. It can be seen that although more and more emerging algorithms have been applied to the analysis of macro driving style in recent years, only a few of these have been applied to the research of vehicle UBI products, which means that there is still a long way to go to regard the risk level of macro driving style as a dimension of premium determination in-vehicle UBI products.

Table 3. Research on differentiated macro driving style.

Research Objects	Detailed Research Objects	Research Focus/Methodologies		Literatures
Differentiated macro driving style	Types of Macro driving style	Style formation factors		[86]
		Style type division	2 style types	[87]
			3 style types	[88–90]
			8 style types	[91]
		Similarity driving behavior clustering		[92]
	Specific driving style identification and classification methodologies	Radical or aggressive drivers identification		[93–96]
		Style classification based on ML algorithms		[97,98]
	Driving style classification based on different purpose	Road condition identification		[99]
		Energy consumption (parameters considered)	64 utilized	[100]
			31 utilized	[101]
			24 utilized	[102]
			2 utilized	[103]
		Energy consumption	Style evaluation state vector	[104]
			Homogeneous Markov model	[105]
			Setting a set of evaluation indices	[106]
	Macro driving style classification specific for UBI products	Relationship between driving mileage and risk		[107]
		Premium determination based on modification of model in traditional commercial vehicle insurance product		[108]
		Fuzzy MCDM evaluation model for PHYD		[109]
		Driving style clustering		[110,111]

4. Design of Vehicle UBI Products

4.1. Research on Types of Policyholder and Implementation Methods of Vehicle UBI Products

Vehicle UBI will no longer treat all premiums of similar vehicle models equally as traditional commercial vehicle insurance products but will fluctuate on the basis of the original premium according to the driving behavior of policyholders. Finkelstein et al. have clearly pointed out in their research that the policyholders are different from each other and have different attitudes towards risk [112]. It is easy to see that the differentiated premium will inevitably lead to the speculative behavior of policyholders with different purchase psychology in the implementation process of vehicle UBI products. Therefore, dividing different types of insurance users and discussing the implementation methods of vehicle UBI products are of great significance for insurance companies to control risks, and maximize product benefits.

Generally, policyholders can be roughly divided into two categories. One is "risk positive" users, who are risk-averse and often actively buy all kinds of insurance products; the other is "risk negative" users, who are not sensitive to the existence of risk unless the risk is large enough to a specific extent. For the research on "risk positive" users, Hemenway described their common characteristics and believed that they belong to high-quality users for insurance companies, their behavior habit is to avoid risks, so they will not bring too many risks to insurance companies [113]; and Dedonder et al. have also pointed out that risk positive users are willing to insure, whether they are at risk or not [114].

As mentioned above, policyholders of different risk types will show different attitudes and even speculation in the process of choosing vehicle insurance products, and speculation is the risk cost that insurance companies need to control. Especially when information and communication technology is not introduced, or when the risk of insured vehicles is evaluated at the beginning of the implementation of vehicle UBI products, insurance companies can only master the limited basic driving data, or just the driving skill statement of policyholders. In these cases, the control of speculative risk is particularly important. Cohen emphasized in his research that the biggest problem in the implementation of differentiated policies based on vehicle UBI is the information asymmetry between policyholders and insurance companies [115]. Of course, studies by Corbett, Lajunen et al., Dunning et al., and Horswill et al. have also shown that information asymmetry sometimes does not necessarily come from the difference in the risk types of policyholders, but from the overestimation of policyholders' driving skills, and they have also pointed out that drivers generally believe that their driving skills are higher than the general level [116–119]. To eliminate the impact of speculation on the risk expenditure of insurance companies, Sundstrom tried to establish a mapping relationship between drivers' description of each micro-operation skill in driving and its driving risk assessment and have found the actual hidden risks of policyholders in the form of a questionnaire survey on driving operation [120].

In addition to the research on the implementation strategy of vehicle UBI products to eliminate speculative risks as much as possible, there are many studies on the implementation scheme of vehicle UBI products themselves. Zantema et al. have pointed out that the joint assessment of driving risk by PAYD and PHYD has strong objectivity, at the same time, they have especially studied the discount mechanism of vehicle UBI products and have given a reasonable discount range for low-risk customers [121]. Handel et al. have proposed an implementation scheme of vehicle UBI products based on smartphones, to encourage users to use vehicle UBI products based on behavior data collected by the mobile client, their scheme considers both driving behavior and smartphone client usage in the underwriting cycle when calculating the premium [122]. Nai et al. proposed an "either-or" initial implementation strategy for PHYD products for both cautious and reckless drivers and have divided the policyholders into 4 quadrants into two dimensions of user division and contract implementation, as shown in Figure 2. Through theoretical analysis, they have demonstrated their ability to provide the maximum utility for the insured vehicles and ensure the reliable profit of the insurance company [123]. It can be seen that in the environment of information asymmetry between policyholders and insurance companies, more research is required on the implementation of vehicle UBI products, so that the evaluation results of differentiated driving styles can be fully supported in the product implementation stage.

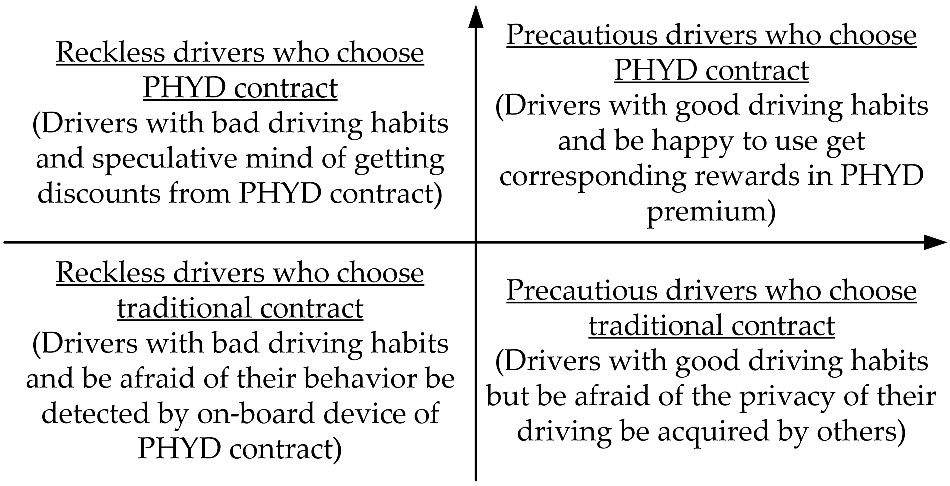

Figure 2. Contract choice in the early stage of implementing PHYD policy with traditional vehicle insurance contract coexisted, Reprinted with permission from Ref. [123].

In terms of the implementation of vehicle UBI products, it should also be pointed out that with the gradual popularization of semi-autonomous and autonomous vehicles, they are gradually bringing changes to the commercial vehicle insurance industry. On the positive side, vehicle accidents will be significantly reduced, but on the negative side, the identification of accident responsibility will become more complex, and the subject of responsibility for accidents will no longer be just the driver, but the original equipment manufacturers (OEMs) and their developers as well. In recent years, some scholars have discussed the identification methods of accident liability for semi-autonomous and autonomous vehicles [124], and some scholars have also studied the driving risk quantification methods for them [125,126]. However, only literature [126] mentioned the UBI product form of an autonomous vehicle. It can be seen that in the era of autonomous vehicles, there are still many thorny issues required to be further studied, including the definition of responsibility subject, product form design, and the coexistence mode of manual driving and autonomous vehicle UBI products, etc.

4.2. Research on the Architecture of Data Processing System for Vehicle UBI

The implementation of vehicle UBI products depends on mastering the information of insured vehicles, especially when implementing vehicle UBI insurance products based on the PHYD concept. Real-time collection of vehicle driving data is a necessary means to fully grasp the information of policyholders and then analyze their risk types [127]. Therefore, UBI data processing architecture is essential in the implementation of vehicle UBI products. Basically, the architecture should include an on-board data transceiver module for user-driving data acquisition, a data transmission channel, and a remote data center for data analysis and application, during recent years, in combination with the latest edge computing technology, some scholars have also transformed this architecture as "end-edge-cloud" based on the concept of IoV [128], its system structure for vehicle UBI products can be shown in Figure 3.

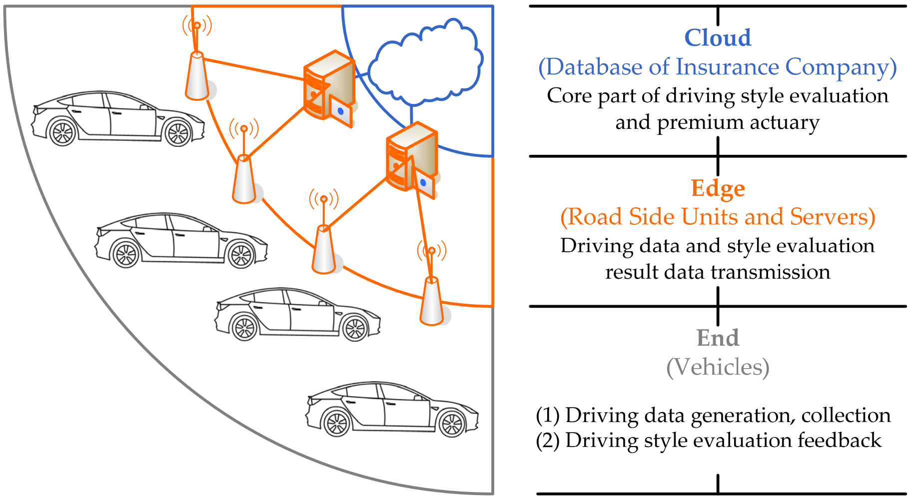

Figure 3. Basic structure of data processing system for vehicle UBI products [128].

The development of smartphones also has an impact on the data processing system architecture of vehicle UBI products and forms a new deformation form based on the system architecture shown in Figure 3. Handel has pointed out that smartphones can replace the onboard data transceiver module as the driving behavior data acquisition terminal [129]. Sathyanarayana et al. have mentioned that the smartphone can not only collect basic driving data such as speed and mileage through the cellular mobile network but also obtain other information such as vehicle altitude. It can make the evaluation more accurate, and the use of a smartphone is easier to be accepted by people than the installation of an on-board data transceiver module [130]. Azzopardi et al. have pointed out that remote communication can bring new vitality to the traditional premium actuary system and establish a new product form of insurance even for vehicle fleets of companies [131]. Handel et al. have pointed out that smartphones can provide an extensible solution for vehicle insurance, drivers can check the dynamic description of the risk level, and the dynamic calculation of the premium is determined by the dynamic sensing based on the time, place and mode of travel realized by UBI applications on smartphones [132]. Li et al. have made full use of smartphone-embedded accelerometers and gyroscope sensors to provide a more rational method for premium calculation of vehicle UBI products [133].

It can be seen that with the development of wireless communication technology, emerging edge computing, and other technologies, the data processing architecture of vehicle UBI products can be carried out through the cooperation of the vehicle end layer, edge layer, and cloud layer. Just as described in Section 3.1.2, while becoming an important driving data collection tool, smartphones can also implement the relevant calculation rules in the vehicle UBI products, which can be linked with the local policies of the edge layer and the global policies of the cloud layer according to the needs of the insurance company. A sound data processing architecture can provide a more accurate and fair hardware foundation for the development of vehicle UBI products.

5. Conclusions and Comments

Due to the fact that the risk evaluation method of vehicle UBI products based on different driving styles reflected by dynamic driving parameters, is not yet fully mature or involves trade secrets, there is no unified standard so far. Therefore, for the vehicle UBI industry, the relevant risk assessment technology can be described as "a hundred schools of thought", and there is still no absolute authority. In addition, due to the different geographical conditions and cultures of various countries, the driving style influencing factors to be considered in the corresponding vehicle UBI products are also different. To implement vehicle UBI products in any country, it is also important to find a set of targeted evaluation methods that can objectively and rationally evaluate regional cultural differences as well as driving behavior. Moreover, to make the core driving risk evaluation method properly play its role, it also needs to cooperate with a reasonable implementation scheme and a sound system architecture design.

Based on the comprehensive discussion of the driving style evaluation method considering various factors and the design of commercial vehicle UBI products in this paper, it can be found that from the research on the characteristics of policyholders and the implementation scheme, to the research on system architecture design of vehicle UBI products related data transmission, processing, and analysis, from the research on the micro behavior and macro driving style of vehicle drivers, to the research on the core method of driving risk evaluation for different driving styles, a complete theoretical framework has not yet been formed. For the research on just one aspect of driving behavior, although there are some mature research methods and research results reported, their directionality for the application in differentiated commercial vehicle insurance is not very clear, and the corresponding research methods cannot be copied or mapped to the research on vehicle UBI products. Therefore, the current situation, challenge, and future research directions of vehicle UBI products can be summarized as follows:

(1) As the driving risk assessment based on driving style will eventually be applied to vehicle UBI products, which will involve the vital economic interests of policyholders, insurance companies have been very cautious about the application of corresponding driving risk assessment algorithms in the past decades, but it is certain that scholars' research on a more objective evaluation of driving risks reflected by different driving styles has never stopped. Although some studies on driving style recognition have not been directly applied to automobile insurance products, the evaluation of driving risk is also involved.

(2) The rapid development of information and communication technology, the popularity of smartphones and smart terminals, and the application of artificial intelligence algorithms aimed at classification are the main characteristics of the times with the development of the Internet of vehicles in recent years. In this context, the driving risk evaluation methods, especially the dynamic risk evaluation methods based on driving style suitable for vehicle UBI products based on new forms of driving data collection, namely the deep correlation between driving data, driving style and even driving risk, is worth to be further explored and developed.

(3) To some extent, differentiated commercial vehicle insurance involves ethical issues and discrimination against some types of people, therefore, its implementation in different countries and regions will undoubtedly be subject to some policy constraints. In addition, as the core methodology of driving risk assessment, in-vehicle UBI products often involve the business secrets of an actuary, even if some scholars are engaged in this research area, the related methodologies have been rarely disclosed. Moreover, the penetration of autonomous vehicles brings more unknown factors and greater uncertainties to the design and implementation of vehicle UBI products, therefore, there is still a long way to go for vehicle UBI products to form a widely accepted product form.

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References

1. Dijksterhuis, C.; Lewis-Evans, B.; Jelijs, B.; de Waard, D.; Brookhuis, K.; Tucha, O. The impact of immediate or delayed feedback on driving behaviour in a simulated Pay-As-You-Drive system. *Accid. Anal. Prev.* **2015**, *75*, 93–104. [CrossRef] [PubMed]
2. Agerholm, N.; Waagepetersen, R.; Tradisauskas, N.; Harms, L.; Lahrmann, H. Preliminary results from the Danish Intelligent Speed Adaptation Project Pay As You Speed. *IET Intell. Transp. Syst.* **2008**, *2*, 143–153. [CrossRef]
3. Nai, W.; Zhang, F.; Dong, D.; Chen, Y.; Yu, Y.; Zheng, W. Fuzzy Risk Mode and Effect Analysis Based on Raw Driving Data for Pay-How-You-Drive Vehicle Insurance. In Proceedings of the IEEE International Conference on Big Data Analysis (ICBDA), Hangzhou, China, 12–14 March 2016. [CrossRef]
4. Litman, T. Pay-As-You-Drive Pricing and Insurance Regulatory Objectives. *J. Insur. Regul.* **2005**, *23*, 35–53.
5. Tselentis, D.I.; Yannis, G.; Vlahogianni, E.I. Innovative Insurance Schemes: Pay as/how You Drive. *Transp. Res. Procedia* **2016**, *14*, 362–371. [CrossRef]
6. Courtney, M. Premium binds. *Eng. Technol.* **2013**, *8*, 68–73. [CrossRef]
7. Progressive. Available online: https://progressiveic.com/en/commercial-insurance/motor-insurance (accessed on 14 June 2022).
8. OnStar. Available online: https://www.onstar.com/us/en/home (accessed on 14 June 2022).
9. Be Wiser Insurance. Available online: https://www.coverbox.co.uk (accessed on 14 June 2022).
10. Octo Connected Forum. Available online: https://www.octotelematics.com (accessed on 14 June 2022).
11. Alles Voor Een Betere Kolometer. Available online: https://www.bovagautoverzekering.nl (accessed on 14 June 2022).
12. Desyllasa, P.; Sako, M. Profiting from business model innovation: Evidence from Pay-As-You-Drive auto insurance. *Res. Policy* **2013**, *42*, 101–106. [CrossRef]
13. Greenberg, A. Designing pay-per-mile auto insurance regulatory incentives. *Transp. Res. Part D Transp. Environ.* **2009**, *14*, 437–445. [CrossRef]
14. Edlin, A.S.; Mandic, P.K. The Accident Externality from Driving. *J. Political Econ.* **2006**, *114*, 931–955. [CrossRef]
15. Parry, I.W.H. Comparing Alternative Policies to Reduce Traffic Accidents. *J. Urban Econ.* **2004**, *54*, 346–368. [CrossRef]
16. Bolderdijk, J.W.; Knockaert, J.; Steg, E.M.; Verhoef, E.T. Effects of pay-as-you-drive vehicle insurance on young drivers' speed choice: Results of a Dutch field experiment. *Accid. Anal. Prev.* **2011**, *43*, 1181–1186. [CrossRef]
17. Dijksterhuis, C.; Lewis-Evans, B.; Tucha, O.; de Waard, D.; Brookhuis, K. In-car usage-based insurance feedback strategies. A comparative driving simulator study. *Ergonomics* **2016**, *59*, 1158–1170. [CrossRef] [PubMed]
18. Doshi, A.; Trivedi, M.M. Examining the impact of driving style on the predictability and responsiveness of the driver: Real-world and simulator analysis. In Proceedings of the IEEE Intelligent Vehicles Symposium (IV), La Jolla, CA, USA, 21–24 June 2010. [CrossRef]
19. Schorr, J.; Hamdar, S.H.; Silverstein, C. Measuring the safety impact of road infrastructure systems on driver behavior: Vehicle instrumentation and real world driving experiment. *J. Intell. Transp. Syst.* **2017**, *21*, 364–374. [CrossRef]
20. Wang, J.; Xiong, C.; Lu, M.; Li, K. Longitudinal driving behaviour on different roadway categories: An instrumented-vehicle experiment, data collection and case study in China. *J. Intell. Transp. Syst.* **2015**, *9*, 555–563. [CrossRef]
21. Li, E.; He, W.; Yu, H.; Xi, J. Model-based embedded road grade estimation using quaternion unscented Kalman filter. *IEEE Trans. Veh. Technol.* **2022**, *71*, 3704–3714. [CrossRef]
22. Nai, W.; Sheng, C.; Liu, Y.; Xing, Y.; Yang, Z. Optimized Road Status Level Grading Method in Driving Style Evaluation for Pay-How-You-Drive Commercial Vehicle Insurance. In Proceedings of the 13th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 12–13 December 2020. [CrossRef]
23. Shi, Y.; Boffi, M.; Piga, B.E.A.; Mussone, L.; Caruso, G. Perception of driving simulations: Can the level of detail of virtual scenarios affect the driver's behavior and emotions? *IEEE Trans. Veh. Technol.* **2022**, *71*, 3429–3442. [CrossRef]
24. Goedicke, D.; Zolkov, C.; Wise, T.; Parush, A.; Ju, W. Strangers in a strange land: New experimental system for understanding driving culture using VR. *IEEE Trans. Veh. Technol.* **2022**, *71*, 3399–3413. [CrossRef]
25. Dixit, V.V.; Gayah, V.V.; Radwan, E. Comparison of driver behavior by time of day and wet pavement conditions. *J. Transp. Eng.* **2012**, *138*, 1023–1029. [CrossRef]
26. Weng, S.; Kodagoda, S.; Shi, L.; Wang, H. Road-terrain classification for land vehicles: Employing an acceleration-based approach. *IEEE Veh. Technol. Mag.* **2017**, *12*, 34–41. [CrossRef]
27. Chu, T.D.; Miwa, T.; Morikawa, T. Discrete choice models for gap acceptance at urban expressway merge sections considering safety, road geometry, and traffic conditions. *J. Transp. Eng.* **2017**, *143*, 04017025. [CrossRef]
28. Guerrier, M.; Mauro, R.; Parla, G.; Tollazzi, T. Analysis of kinematic parameters and driver behavior at turbo roundabouts. *J. Transp. Eng. Part A Syst.* **2018**, *144*, 04018020. [CrossRef]
29. Okuda, H.; Suzuki, T.; Harada, K.; Saigo, S.; Inoue, S. Quantitative driver acceptance modeling for merging car at highway junction and its application to the design of merging behavior control. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 329–340. [CrossRef]
30. Gao, H.; Hu, C.; Xie, G.; Han, C. Discretionary cut-in driving behavior risk assessment based on naturalistic driving data. *IEEE Intell. Transp. Syst. Mag.* **2022**, *14*, 29–40. [CrossRef]

31. Ma, Y.; Yin, B.; Jiang, X.; Du, J.; Chan, C. Psychological and environmental factors affecting driver's frequent lane-changing behaviour: A national sample of drivers in China. *IET Intell. Transp. Syst.* **2020**, *14*, 825–833. [CrossRef]
32. Wang, Y.; Xu, W.; Zhang, W.; Zhao, J.L. SafeDrive: A new model for driving risk analysis based on crash avoidance. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 2116–2129. [CrossRef]
33. Parker, D.; Lajunen, T.; Stradling, S. Attitudinal predictionrs of interpersonally aggressive violations on the road. *Transp. Res. Part F Traffic Psychol. Behav.* **1998**, *1*, 11–24. [CrossRef]
34. Lajunen, T.; Parker, D. Are aggressive people aggressive drivers? A study of the relationship between self-reported general aggressiveness, driver anger and aggressive driving. *Accid. Anal. Prev.* **2001**, *33*, 243–255. [CrossRef]
35. Xie, C.Q.; Parker, D. A social psychological approach to driving violations in two Chinese cities. *Transp. Res. Part F Traffic Psychol. Behav.* **2002**, *5*, 293–308. [CrossRef]
36. Ozkan, T.; Lajunen, T.; Summala, H. Driver behavior questionnaire: A follow-up study. *Accid. Anal. Prev.* **2006**, *38*, 386–395. [CrossRef]
37. Laapotti, S.; Keskinen, E.; Rajalin, S. Comparison of young male and female drivers' attitude and self-reported behavior in Finland in 1978 and 2001. *J. Saf. Res.* **2003**, *34*, 579–587. [CrossRef]
38. Donmez, B.; Boyle, L.N.; Lee, J.D. Differences in off-road glances: Effects on young drivers' performance. *J. Transp. Eng.* **2010**, *136*, 403–409. [CrossRef]
39. Freund, B.; Colgrove, L.A.; Burke, B.L.; McLeod, R. Self-rated driving performance among elderly drivers referred for driving evaluation. *Accid. Anal. Prev.* **2005**, *37*, 613–618. [CrossRef] [PubMed]
40. Lyu, N.; Wang, Y.; Wu, C.; Wu, H.; Wen, J. Exploring longitudinal driving behaviour on a freeway deceleration lane using field operational test data. *IET Intell. Transp. Syst.* **2021**, *15*, 1401–1413. [CrossRef]
41. West, R.; Elander, J.; French, D. Mild social deviance, Type-A behavior pattern and decision-making style as predictors of self-reported driving style and traffic accident risk. *Br. J. Psychol.* **1993**, *84*, 207–219. [CrossRef]
42. Garrity, R.D.; Demick, J. Relations among personality traits, mood states, and driving behaviours. *J. Adult Dev.* **2001**, *8*, 109–118. [CrossRef]
43. Lajunen, T.; Parker, D.; Summala, H. The Manchester driver behavior questionnaire: A cross-cultural study. *Accid. Anal. Prev.* **2004**, *36*, 231–238. [CrossRef]
44. Hartos, J.; Eitel, P.; Simons-Morton, B. Parenting practices and adolescent risky driving: A three-month prospective study. *Health Educ. Behav.* **2002**, *29*, 194–206. [CrossRef]
45. Beck, K.H.; Hartos, J.; Simons-Morton, B. Teen driving risk: The promise of parental influence and public policy. *Health Educ. Behav.* **2002**, *29*, 73–84. [CrossRef]
46. Bianchi, A.; Summala, H. The 'genetics' of driving behavior: Parents' driving style predicts their children's driving style. *Accid. Anal. Prev.* **2004**, *36*, 655–659. [CrossRef]
47. Mckay, M.P.; Coben, J. Attitudes of novice teen drivers and parents about Pennsylvania's graduated driver licensing program: A focus group analysis. *Traffic Inj. Prev.* **2002**, *3*, 257–261. [CrossRef]
48. Shope, J.T.; Waller, P.F.; Raghunathan, T.E.; Patil, S.M. Adolescent antecedents of high-risk driving behavior into young adulthood: Substance use and parental influences. *Accid. Anal. Prev.* **2001**, *23*, 649–658. [CrossRef]
49. Westerman, S.J.; Haigney, D. Individual differences in driver stress, error, and violations. *Personal. Individ. Differ.* **2000**, *29*, 981–998. [CrossRef]
50. Lanata, A.; Valenza, G.; Greco, A.; Gentili, C.; Bartolozzi, R.; Bucchi, F.; Frendo, F.; Scilingo, E.P. How the autonomic nervous system and driving style change with incremental stressing conditions during simulated driving. *IEEE Trans. Intell. Transp. Syst.* **2015**, *16*, 1505–1517. [CrossRef]
51. Yang, Y.; Wong, A.; McDonald, M. Does gender make a difference to performing in-vehicle tasks? *IET Intell. Transp. Syst.* **2015**, *9*, 359–365. [CrossRef]
52. Danaf, M.; Abou-Zeid, M.; Kaysi, I. Modeling anger and aggressive driving behavior in a dynamic choice-latent variable model. *Accid. Anal. Prev.* **2015**, *75*, 105–118. [CrossRef] [PubMed]
53. Magana, V.C.; Munoz-Organero, M. Toward safer highways predicting driver stress in varying conditions on habitual routes. *IEEE Veh. Technol. Mag.* **2017**, *12*, 69–76. [CrossRef]
54. Kim, H.S.; Yoon, D.; Shin, H.S.; Park, C.H. Predicting the EEG Level of a Driver Based on Driving Information. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 1215–1225. [CrossRef]
55. Requardt, A.F.; Ihme, K.; Wilbrink, M.; Wendemuth, A. Towards affect-aware vehicles for increasing safety and comfort: Recognising driver emotions from audio recordings in a realistic driving study. *IET Intell. Transp. Syst.* **2020**, *14*, 1265–1277. [CrossRef]
56. Wang, X.; Guo, Y.; Bai, C.; Yuan, Q.; Liu, S.; Han, J. Driver's intention identification with the involvement of emotional factors in two-lane roads. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 6866–6874. [CrossRef]
57. Grabarek, I.; Bęczkowska, S. Analysis of Factors Determining Ergonomic Conditions of Driver's Workplace and Safety in Transport of Dangerous Goods. *Arch. Transp.* **2012**, *24*, 297–306. [CrossRef]
58. Wang, Z.; Zheng, R.; Kaizuka, T.; Nakano, K. Influence of haptic guidance on driving behavior under degraded visual feedback conditions. *IET Intell. Transp. Syst.* **2018**, *12*, 454–462. [CrossRef]

59. Roche, F.; Brandenburg, S. Should the urgency of visual-tactile takeover requests match the criticality of takeover situations? *IEEE Trans. Intell. Veh.* **2020**, *5*, 306–313. [CrossRef]
60. Horswill, M.S.; Coster, M.E. The effect of vehicle characteristics on drivers' risk-taking behavior. *Ergonomics* **2002**, *45*, 85–104. [CrossRef] [PubMed]
61. Colombaroni, C.; Fusco, G.; Isaenko, N. Coherence analysis of road safe speed and driving behaviour from floating car data. *IET Intell. Transp. Syst.* **2020**, *14*, 985–992. [CrossRef]
62. Liu, Y.; Hansen, J.H.L. A review of UTDrive studies: Learning driver behavior from naturalistic driving data. *IEEE Open J. Intell. Transp. Syst.* **2021**, *2*, 338–346. [CrossRef]
63. Hu, X.; Zhu, X.; Ma, Y.-L.; Chiu, Y.-C.; Tang, Q. Advancing usage-based insurance—A contextual driving risk modeling and analysis approach. *IET Intell. Transp. Syst.* **2019**, *13*, 453–460. [CrossRef]
64. Bejani, M.M.; Ghatee, M. Convolutional neural network with adaptive regularization to classify driving styles on smartphones. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 543–552. [CrossRef]
65. Martinez, C.M.; Heucke, M.; Wang, F.-Y. Driving style recognition for intelligent vehicle control and advanced driver assistance: A survey. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 666–676. [CrossRef]
66. Barabino, B.; Coni, M.; Olivo, A.; Pungillo, G.; Rassu, N. Standing passenger comfort: A new scale for evaluating the real-time driving style of bus transit services. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 4665–4678. [CrossRef]
67. Mata-Carballeira, O.; del Campo, I.; Asua, E. An eco-driving approach for ride comfort improvement. *IET Intell. Transp. Syst.* **2022**, *16*, 186–205. [CrossRef]
68. Wang, W.; Liu, C.; Zhao, D. How much data are enough? A statistical approach with case study on longitudinal driving behavior. *IEEE Trans. Intell. Veh.* **2017**, *2*, 85–97. [CrossRef]
69. Liu, T.; Selpi. Comparison of car-following behavior in terms of safety indicators between China and Sweden. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 3595–3705. [CrossRef]
70. Cheng, X.; Zhou, J.; Zhao, X. Safety assessment of vehicle behaviour based on the improved D–S evidence theory. *IET Intell. Transp. Syst.* **2020**, *14*, 1396–1402. [CrossRef]
71. Yin, J.-L.; Chen, B.-H.; Lai, K.-H.R. Driver danger-level monitoring system using multi-sourced big driving data. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 5271–5282. [CrossRef]
72. Liu, C.; Zhang, W. Learning the driver acceleration/deceleration behavior under high-speed environments from naturalistic driving data. *IEEE Intell. Transp. Syst. Mag.* **2022**, *14*, 78–91. [CrossRef]
73. Llorca, C.; García, A.; Moreno, A.T.; Perez-Zuriaga, A.M. Influence of age, gender and delay on overtaking dynamics. *IET Intell. Transp. Syst.* **2013**, *7*, 174–181. [CrossRef]
74. Xu, L.; Hu, J.; Jiang, H.; Meng, W. Establishing style-oriented driver models by imitating human driving behaviors. *IEEE Trans. Intell. Transp. Syst.* **2015**, *16*, 2522–2530. [CrossRef]
75. Fugiglando, U.; Massaro, E.; Santi, P.; Milardo, S.; Abida, K.; Stahlmann, R.; Netter, F.; Ratti, C. Driving behavior analysis through CAN bus data in an uncontrolled environment. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 737–748. [CrossRef]
76. Christopoulos, S.G.; Kanarachos, S.; Chroneos, A. Driver braking behavior using smartphones, neural networks and the sliding correlation coefficient: Road anomaly case study. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 65–74. [CrossRef]
77. Cheng, Q.; Jiang, X.; Wang, W.; Cietrich, A.; Bengler, K.; Qin, Y. Analyses on the heterogeneity of car-following behaviour: Evidence from a cross cultural driving simulator study. *IET Intell. Transp. Syst.* **2020**, *14*, 834–841. [CrossRef]
78. Chen, Y.; Zhang, Y.; Zhang, F. Personalized path generation and robust H_∞ output-feedback path following control for automated vehicles considering driving styles. *IET Intell. Transp. Syst.* **2021**, *15*, 1582–1595. [CrossRef]
79. Zheng, W.; Nai, W.; Zhang, F.; Qin, W.; Dong, D. A Novel Set of Driving Style Risk Evaluation Index System for UBI Based Differentiated Commercial Vehicle Insurance in China. In Proceedings of the 15th COTA International Conference of Transportation Professionals (CICTP), Beijing, China, 24–27 July 2015. [CrossRef]
80. Nai, W.; Zhang, F.; Dong, D.; Chen, Y.; Yu, Y.; Zheng, W. Effective Presenting Method for Different Driving Styles Based on Hexagonal Eye Diagram Applied in Pay-How-You-Drive Insurance. In Proceedings of the IEEE International Conference on Big Data Analysis (ICBDA), Hangzhou, China, 12–14 March 2016. [CrossRef]
81. Chen, Z.; Wu, C.; Huang, Z.; Lyu, N.; Hu, Z.; Zhong, M.; Cheng, Y.; Ran, B. Dangerous driving behavior detection using video-extracted vehicle trajectory histograms. *J. Intell. Transp. Syst.* **2017**, *21*, 409–421. [CrossRef]
82. Yan, L.; Huang, Z.; Zhang, Y.; Zhang, L.; Zhu, D.; Ran, B. Driving risk status prediction using Bayesian networks and logistic regression. *IET Intell. Transp. Syst.* **2017**, *11*, 431–439. [CrossRef]
83. Han, W.; Wang, W.; Li, X.; Xi, J. Statistical-based approach for driving style recognition using Bayesian probability with kernel density estimation. *IET Intell. Transp. Syst.* **2019**, *13*, 22–30. [CrossRef]
84. He, X.; Xu, L.; Zhang, Z. Driving behaviour characterisation by using phase-space reconstruction and pre-trained convolutional neural network. *IET Intell. Transp. Syst.* **2019**, *13*, 1173–1180. [CrossRef]
85. Liao, L.; Chen, B.; Zou, F.; Li, S.E.; Liu, J.; Wu, X.; Dong, N. Hierarchical quantitative analysis to evaluate unsafe driving behaviour from massive trajectory data. *IET Intell. Transp. Syst.* **2020**, *14*, 849–856. [CrossRef]
86. French, D.J.; West, R.J.; Elander, J.; Wilding, J.M. Decision-Making style, driving style, and self-reported involvement in road traffic accidents. *Ergonomics* **1993**, *36*, 627–644. [CrossRef]

87. Johnson, D.A.; Trivedi, M.M. Driving style recognition using a smartphone as a sensor platform. In Proceedings of the 14th International IEEE Conference on Intelligent Transportation Systmes (ITSC), Washington, DC, USA, 5–7 October 2011. [CrossRef]
88. Tricot, N.; Sonnerat, D.; Popieul, J.C. Driving styles and traffic density diagnosis in simulated driving conditions. In Proceedings of the IEEE Intelligent Vehicles Symposium (IV), Versailles, France, 17–21 June 2002. [CrossRef]
89. Qi, G.; Du, Y.; Wu, J.; Xu, M. Leveraging longitudinal driving behaviour data with data mining techniques for driving style analysis. *IET Intell. Transp. Syst.* **2015**, *9*, 792–801. [CrossRef]
90. Yang, K.; Al Haddad, C.; Yannis, G.; Antoniou, C. Classification and evaluation of driving behavior safety levels: A driving simulation study. *IEEE Open J. Intell. Transp. Syst.* **2022**, *3*, 111–125. [CrossRef]
91. Taubman-Ben-Ari, O.; Mikulincer, M.; Gillath, O. The multidimentional driving style inventory—Scale construct and validation. *Accid. Anal. Prev.* **2004**, *36*, 323–332. [CrossRef]
92. Wang, W.; Han, W.; Na, X.; Gong, J.; Xi, J. A probabilistic approach to measuring driving behavior similarity with driving primitives. *IEEE Trans. Intell. Veh.* **2020**, *5*, 127–138. [CrossRef]
93. Boyce, T.E.; Geller, E.S. An instrumental vehicle assessment of problem behavior and driving style: Do younger males really take nore risks? *Accid. Anal. Prev.* **2002**, *34*, 51–64. [CrossRef]
94. Musselwhite, C. Attitudes towards vehicle driving behavior: Categorizing and contextualizing risk. *Accid. Anal. Prev.* **2006**, *38*, 324–334. [CrossRef] [PubMed]
95. Cura, A.; Kucuk, H.; Ergen, E.; Oksuzoglu, I.B. Driver profiling using long short term memory (LSTM) and convolutional neural network (CNN) Methods. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 6572–6582. [CrossRef]
96. Gatteschi, V.; Cannavo, A.; Lamberti, F.; Morra, L.; Montuschi, P. Comparing algorithms for aggressive driving event detection based on vehicle motion data. *IEEE Trans. Veh. Technol.* **2022**, *71*, 53–68. [CrossRef]
97. Abdelrahman, A.E.; Hassanein, H.S.; Abu-Ali, N. Robust data-driven framework for driver behavior profiling using supervised machine learning. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 3336–3350. [CrossRef]
98. Yuksel, A.S.; Atmaca, S. Driver's black box: A system for driver risk assessment using machine learning and fuzzy logic. *J. Intell. Transp. Syst.* **2021**, *25*, 482–500. [CrossRef]
99. Huang, X.; Tan, Y.; He, X. An intelligent multifeature statistical approach for the discrimination of driving conditions of a hybrid electric vehicle. *IEEE Trans. Intell. Transp. Syst.* **2011**, *12*, 453–465. [CrossRef]
100. Ericsson, E. Independent driving pattern factors and their influence on fuel-use and exhaust emission factors. *Transp. Res. Part D Transp. Environ.* **2001**, *6*, 325–345. [CrossRef]
101. Langari, R.; Won, J.-S. Intelligent energy management agent for a parallel hybrid vehicle—Part I: System architecture and design of the driving situation identification process. *IEEE Trans. Veh. Technol.* **2005**, *54*, 925–934. [CrossRef]
102. Jeon, S.; Jo, S.; Park, Y.; Lee, J. Multi-mode driving control of a parallel hybrid electric vehicle using driving pattern recognition. *J. Dyn. Syst. Meas. Control.* **2002**, *124*, 141–149. [CrossRef]
103. Lin, C.; Jeon, S.; Peng, H.; Lee, J.M. Driving pattern recognition for control of hybrid electric trucks. *Veh. Syst. Dyn.* **2004**, *42*, 41–58. [CrossRef]
104. Lin, C.; Peng, H.; Grizzle, J.W. A Stochastic Control Strategy for Hybrid Electric Vehicles. In Proceedings of the American Control Conference (ACC), Boston, MA, USA, 30 June–2 July 2004. [CrossRef]
105. Johannesson, L.; Asbogard, M.; Egardt, B. Assessing the Potential of Predictive Control for Hybrid Vehicle Powertrains Using Stochastic Dynamic Programming. *IEEE Trans. Intell. Transp. Syst.* **2007**, *8*, 71–83. [CrossRef]
106. Tanoue, S.; Higuchi, H. Driving Evaluation Method. U.S. Patent No. US8565964, 22 October 2013.
107. Cripe, F.H.; Fiete, S. Usage-Based Insurance Cost Determination System and Method. U.S. Patent No. US8812330B1, 19 August 2014.
108. Walcott-Bryant, A.; Tatsubori, M.; Bryant, R.E.; Oduor, E.; Omondi, S.; Osebe, S.; Wamburu, J.; Bent, O. Harsh brakes at potholes in Nairobi: Context-based driver behavior in developing cities. In Proceedings of the IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), Rio de Janeiro, Brazil, 1–4 November 2016. [CrossRef]
109. Wang, C.; Liu, J.; Li, H.; Nai, W.; Zheng, W. Driving Risk Evaluation Applied to Premium Actuary for Pay-How-You-Drive Vehicle Insurance Based on Fuzzy Multi Criteria Decision-Making. In Proceedings of the 11th International Conference on Software Engineering and Service Science (ICSESS), Beijing, China, 16–18 October 2020. [CrossRef]
110. Zhang, J.; Lu, H.; Sun, J. Improved driver clustering framework by considering the variability of driving behaviors across traffic operation conditions. *J. Transp. Eng. Part A Syst.* **2021**, *147*, 04022033. [CrossRef]
111. Sun, P.; Wang, X.; Zhu, M. Modeling car-following behavior on freeways considering driving style. *J. Transp. Eng. Part A: Syst.* **2021**, *147*, 04021083. [CrossRef]
112. Finkelstein, A.; McGarry, K. Multiple dimensions of private information: Evidence from the long-term care insurance market. *Am. Econ. Rev.* **2006**, *96*, 938–958. [CrossRef] [PubMed]
113. David, H. Propitious selection. *Q. J. Econ.* **1990**, *105*, 1063–1069. [CrossRef]
114. De Donder, P.; Hindriks, J. Adverse Selection, moral hazard and propitious selection. *J. Risk Uncertain.* **2009**, *38*, 73–86. [CrossRef]
115. Cohen, A. Asymmetric information and learning: Evidence from the automobile insurance market. *Rev. Econ. Stat.* **2005**, *87*, 197–207. [CrossRef]
116. Corbett, C. Explanations for "understanding" in self-reported speeding behavior. *Transp. Res. Part F Traffic Psychol. Behav.* **2001**, *4*, 133–150. [CrossRef]

117. Lajunen, T.; Summala, H. Can we trust self-reports of driving? Effects of impression management on driver behavior questionnaire responses. *Transp. Res. Part F Traffic Psychol. Behav.* **2003**, *6*, 97–107. [CrossRef]
118. Dunning, D.; Health, C.; Suls, J.M. Flawed Self-assessment Implications for Health Education and Workplace. *Psychol. Sci. Public Interest* **2004**, *5*, 69–121. [CrossRef] [PubMed]
119. Horswill, M.S.; Waylen, A.E.; Tofield, M.I. Drivers' ratings of different components of their own driving skill: A greater illusion of superiority for skills that relate to accident involvement. *J. Appl. Soc. Psychol.* **2004**, *34*, 177–195. [CrossRef]
120. Sundstrom, A. Self-assessment of driving skill—A review from a measurement perspective. *Transp. Res. Part F Traffic Psychol. Behav.* **2008**, *11*, 1–9. [CrossRef]
121. Zantema, J.; Van Ameisfort, D.; Bliemer, M.; Bovy, P. Pay-as-you-drive strategies: Case study of safety and accessibity effects. *Transp. Res. Rec.* **2008**, *2078*, 8–16. [CrossRef]
122. Handel, P.; Ohlsson, M.; Skog, I.; Ohlsson, J. Determination of Activity Rate of Portable Electronic Equipment. Europe Patent No. EP2812871A1, 17 December 2014.
123. Nai, W.; Qin, W.; Zhang, F.; Yu, Y.; Dong, D. Contract Strategy Design in Early Stage of Implementing Pay-How-You-Drive Policy with Traditional Commercial Vehicle Insurance Coexisted. In Proceedings of the 12th International Conference on Services Systems and Service Management (ICSSSM), Guangzhou, China, 22–24 June 2015. [CrossRef]
124. Sheehan, B.; Murphy, F.; Ryan, C.; Mullins, M.; Liu, H.Y. Semi-autonomous vehicle motor insurance: A Bayesian network risk transfer approach. *Transp. Res. Part C Emerg. Technol.* **2017**, *82*, 124–137. [CrossRef]
125. Liu, C.; Rouse, W.B.; Belanger, D. Understanding risk and opportunities of autonomous vehicle technology adoption through systems dynamic scenario modeling—The American insurance industry. *IEEE Syst. J.* **2020**, *14*, 1365–1374. [CrossRef]
126. Guillen, M.; Perez-Marin, A.M. The contribution of usage-based data analytics to benchmark semi-autonomous vehicle insurance. In *Mathematical and Statistical Methods for Actuarial Sciences and Finance*; Corazza, M., Durban, M., Grane, A., Perna, C., Sibillo, M., Eds.; Springer: Cham, Switzerland, 2018; pp. 419–423. [CrossRef]
127. Hopkins, J.C. Systems and Methods for Processing Vehicle or Driver Performance Data. U.S. Patent No. US8566126B1, 22 October 2013.
128. Jiang, M.; Wu, T.; Wang, Z.; Gong, Y.; Zhang, L.; Liu, R.P. A multi-intersection vehicular cooperative control based on end-edge-cloud computing. *IEEE Trans. Veh. Technol.* **2022**, *71*, 2459–2471. [CrossRef]
129. Handel, P.; Ohlsson, J.; Ohlsson, M.; Skog, I.; Nygren, E. Smartphone-Based Measurement Systems for Road Vehicle Traffic Monitoring and Usage-Based Insurance. *IEEE Syst. J.* **2014**, *8*, 1238–1248. [CrossRef]
130. Sathyanarayana, A.; Sadjadi, S.O.; Hansen, J.H.L. Leveraging sensor information from portable devices towards automatic driving maneuver recognition. In Proceedings of the 15th International IEEE Conference on Intelligent Transportation Systems (ITSC), Anchorage, AK, USA, 16–19 September 2012. [CrossRef]
131. Azzopardi, M.; Cortis, D. Implementing automotive telematics for insurance covers of fleets. *J. Technol. Manag. Innov.* **2013**, *8*, 59–67. [CrossRef]
132. Handel, P.; Skog, I.; Wahlstrom, J.; Bonawiede, F.; Welch, R.; Ohlsson, J.; Ohlsson, M. Insurance telematics: Opportunities and challenges with the smartphone solution. *IEEE Intell. Transp. Syst. Mag.* **2014**, *6*, 57–70. [CrossRef]
133. Li, F.; Zhang, H.; Che, H.; Qiu, X. Dangerous driving behavior detection using smartphone sensors. In Proceedings of the IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), Rio de Janeiro, Brazil, 1–4 November 2016. [CrossRef]