Innovative Motor Insurance Schemes: A Review of Current Practices and Emerging Challenges

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Abstract

The objective of this paper is to provide a review of the most popular and often implemented methodologies related to Usage-based motor insurance (UBI). UBI schemes, such as Pay-as-you-drive (PAYD) and Pay-how-you-drive (PHYD), are a new innovative concept that has recently started to be commercialized around the world. The main idea is that instead of a fixed price, drivers have to pay a premium based on their travel and driving behaviour. Despite the fact that it has been implemented only for a few years, it appears to be a very promising practice with a significant potential impact on traffic safety as well as on traffic congestion mitigation and pollution emissions reduction. To this end, the existing literature on UBI schemes is reviewed and research gaps are identified. Findings show that there is a multiplicity and diversity of several research studies accumulated in modern literature examining the correlation between PAYD (based on driver's travel behaviour and exposure) and PHYD (based on driving behaviour) schemes and crash risk in order to determine crash risk. Moreover, there is evidence that UBI implementation would eliminate the cross-subsidies phenomenon, which implies less insurance costs for less risky and exposed drivers. It would also provide a strong motivation for drivers to improve their driving behaviour, differentiate their travel behaviour and reduce their degree of exposure by receiving feedback and monitoring their driving preferences and performance, which would result in crash risk reduction both totally and individually. The paper finally discussed the current and emerging challenges on this research field.

Keywords: Pay-as-you-drive; Pay-how-you-drive; Driving behaviour; Travel behaviour and exposure; Crash risk

1. Introduction

Current pricing policy of motor insurance companies around the world which is to charge a lump sum for each user has been for long considered unfair and inefficient (Butler et al., 1988). Drivers with similar characteristics, such as age, gender, etc. pay approximately the same premiums regardless of the distance they drive a year. Bordoff and Noel (2008) compared this approach to a restaurant with an unlimited food policy for a fixed charge per person, which encourages people to eat more. Respectively, current insurance pricing policy encourages driving more kilometres annually, does not punish aggressive driving behaviour and, on the other hand, it does not encourage prudent driving behaviour. But, above all, this implies increased number of crashes, congestion conditions, carbon emissions, local pollution and oil dependence. Current pricing system is unfair because it literally forces drivers with low mileage per year and safer driving behaviour to subsidize the insurance costs for drivers who drive annually more kilometres and in a less safe manner. On the top of that, the research finding that people with lower income drive fewer kilometres leads to the conclusion that existing policies promote social inequities (Litman, 2002).

It should be highlighted that within this review the authors will refer to travel behaviour of the driver as her/his strategic choices (at real-time or not) concerning which type of road network is using and at what time is driving in order to fulfil her/his travel needs. These choices are directly linked to her/his exposition to traffic accident risk, through her/his mileage, the road network type chosen and the related traffic conditions, the period of time chosen to drive and the related weather conditions. Insurance charging systems based on Travel Behaviour are often called Pay As You Drive (PAYD) Usage Based Insurance schemes. On the other hand, this review will refer to driving behaviour of the driver as her/his operational choices at real time in handling her/his vehicle within the existing traffic conditions. These choices are directly linked to the

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probability of getting involved in a traffic accident, based on the way s/he is driving, e.g. by speeding, harsh braking, harsh accelerating, harsh cornering, being distracted by her/his mobile phone, etc. Insurance charging systems based on Driving Behaviour are often called Pay How You Drive (PHUD) Usage Based Insurance schemes.

In general, each driver could be assigned a probability of crash involvement based on his/her driving behaviour. Charging all drivers a lump sum leads to assume that the crash probability is equal across the entire population of drivers. Evidently, this does not from a user optimum and socially equitable approach, as drivers with lower crash risk are forced to "subsidize" those with higher. In other words, less risky drivers are forced to "buy" higher probability of crash risk than actually exists, unlike risky drivers who "buy" less.

An innovative insurance policy could have a significant effect on safety depending on its design (Zantema et al., 2008). Since it could be possible to sort different driving styles on a continuum scale from high to low risk (Sagberg et al., 2015), and therefore create a safety scoring scale, it is a feasible solution to differentiate premiums to reflect safety, more specifically by charging higher fees for unsafe road categories and night-time driving, most effectively and apply it to all drivers. The insurance policy based on vehicle use (Usage Based Insurance or otherwise UBI) includes Pay-As-You-Drive Systems (PAYD) and Pay-How-You-Drive (PHYD). PAYD system is charging premiums based on total travel behaviour characteristics such as mileage and road network used while PHYD is based on individual driving behaviour measuring parameters such as speed, harsh acceleration, hard braking etc. The main data source for the aforementioned parameters are the automotive diagnostic systems, OBD (On-Board Diagnostics), installed in the vehicle and / or the Smartphone held by drivers, sending all necessary information in a central database via mobile network.

The main advantages of UBI schemes compared to the conventional solution offered so far are (Sugarman, 1994, Litman, 2004a, Litman, 2004b):

• Each user will pay as and how he drives, not based on other unfair characteristics such as age, type of car, etc., which do not necessarily reflect the chance of being involved in a crash.

• The need for cross-subsidies (cross-subsidies phenomenon) will be lower and result in a lower and more affordable cost of insurance premiums which would lead to a smaller number of uninsured vehicles.

• This method itself is an incentive for users to improve their driving performance and consequently reduce the number of crashes in which someone causes or gets involved in. It also enables someone to monitor his/her behaviour while driving thus eliminating behaviours that increase the likelihood of causing a crash.

• The implementation of this approach will help reduce the total number of crashes leading ultimately to significantly upgraded road safety.

• With regards to the social benefits, this method will assist driving behaviour improvement and thus reduce pollutants emission, saturation, energy consumption and will generally upgrade transportation system.

An additional benefit offered by UBI schemes is user's feedback on driving behaviour (Toledo et al., 2008) by receiving statistical reports after or while driving such as the percentage of speeding, number of harsh acceleration/ braking events, time driving during risky hours, fuel consumption etc. In this way, UBI may also serve as a mechanism to raise drivers' awareness and change (improve) their driving behaviour. First, because the economic incentive will be strong for him. The premiums will be very high especially for risky drivers so the motivation to drive safer will be very powerful. The same would apply to less risky drivers as well since premiums cost will be reduced because of their good performance. Second, the ability to monitor and compare their own performance from now onwards will assist towards their performance improvement. It is generally shown that (Birrell et al., 2014) an in-vehicle smart driving system, e.g. a smartphone application pointing out frequent mistakes a driver makes while driving, which is developed and designed based on drivers' requirements information can lead to significant improvements in driving behaviours.

A study in the Netherlands showed that, if PAYD were to be implemented, total crash reduction could be reduced more than 5% leading to 60 less fatalities as well as 1000 less injured each year in the Netherlands (Zantema et al., 2008). Research in other countries outside Europe on differentiating premiums indicates the same percentage of 5% mileage reduction on average although driving during low and medium risk hours was only significantly reduced (Reese and Pash, 2009).

The usage-based insurance market was at the starting point of 4.5 million subscribers in 2013, mainly from the United Kingdom, Italy and the US, out of the 1 billion insured vehicles worldwide. This number is expected to be around 100 million by 2020 showing that UBI is a very promising insurance concept (Ptolemus Consulting Group, 2016) and is projected to grow to approximately 50% of the world's vehicles by 2030. UBI is already becoming mainstream in the US and Italy which currently represents 25 to

33% of new business among insurance companies that telematics is their priority (Ptolemus Consulting Group, 2016). Taking also into account the fact that most vehicle manufacturers will have adopted UBI by 2020 (Ptolemus Consulting Group, 2016), it is expected to be rapidly adopted worldwide in the future. Therefore, the future direction is to gradually replace the current homogenized insurance pricing policy with a fairly personalized pricing. As stated above, the development of technology and overcoming impediments that could not be overtaken before make this feasible.

Papers within this research were selected so that the following research questions can be addressed. The papers selected to be reviewed herein discuss the importance of UBI application and its influence on traffic safety, with emphasis on quantitative analysis. They also include the most innovative data collection methods and the indicators used in models developed for data analysis. The following research questions were targeted:

1) Which are the current types of Motor Insurance Schemes, the requirements in data collection and analysis and the most often used techniques to confront with the input parametrization issue?
2) How is UBI anticipated to enhance traffic safety?
3) What could be the evolution of UBI models and which are the future challenges emerging?

The results of this research are presented and discussed in the following sections of this paper.

Papers selected for presentation and discussion within this research were searched in a large set of scientific peer reviewed Journals contained at the ScienceDirect and Google Scholar databases, filtered for papers published in 1970 and after when the concept of UBI was initially discussed and with emphasis on those with quantitative analysis. Papers that were not contributing in addressing the research questions raised above were excluded.

2. Driver’s travel and driving behaviour data collection

Until recently, the high cost of real-time driving data recording systems, data programs, cloud computing services, the inability to accumulate and exploit massive data bases (Big Data) for transport and traffic management purposes (De Romph, 2013, Lee, 2014), as well as the low penetration rate of Smartphones and social networks, made it extremely hard to collect and manage real-time data and, therefore, to study the relation between driving behaviour and travel behaviour and the probability of crash involvement. Research has indicated that barriers like those mentioned above can be overcome when consumers are given an incentive such as a monetary prize (Reese and Pash, 2009); this, along with informing drivers through personalised feedback about their speeding are also effective at encouraging drivers to reduce their (mainly speeding) driving behaviour (Ellison, 2015a). It is shown (Elvik, 2014) that the highest rates in speeding reduction by incentive schemes is around 60-80% while the respective percentage for mileage reduction is 0-10%.

Thus, the main challenge road safety entities and policy-makers are facing at the moment is the wide provision of information on the social benefits that could arise from an implementation of such a policy. As a matter of fact, high level of interest has been observed among users who were given a medium value financial incentive of $88 per 6-months period to reduce their mileage. Consumers stated that lower Insurance premiums is among the strongest incentive for them and that a mileage-based Insurance could probably lead them to ultimately consider car sharing or even using public transportation (Reese and Pash, 2009).

Nowadays, it is feasible to collect high quality real-time data in an efficient way in order to model individual and total crash risk. In terms of the data collection process, data in most studies are recorded either by the vehicle’s OBD (Jensen et al., 2011) or user’s smartphone (Handel et al., 2014) and transmitted to a central database for central processing and analysis (Boquete et al., 2010, Iqbal and Lim, 2006). This allows the development of special indicators for estimating driver’s risk travel (PAYD) and driving (PHYD) behaviour.

In some studies, there exists an on board platform inside the vehicle which acquires and processes data obtained from the GPS, the EOBD system and a mobile-telephone use detection circuit (Boquete et al., 2010). Data are transmitted to a control centre (CC) via a mobile telephone connection, where the risk reflected by each vehicle to the insurance company is estimated. The system uses mobile telephony connection to transmit data between the On-board system (OS) and the CC. Vehicle function data (such as number of seatbelts fastened) are captured from the EOBD system, vehicle position-speed data from the GPS and driver mobile-telephone use data from a detector circuit (RF energy scavenging) are ultimately acquired by the OS. Before transmitting it to the CC, data captured by the OS are processed and stored by a high-performance microcontroller that exists inside the core of the OS.

Other studies also incorporate light or weather sensors that interact via a communications channel (infrared or Bluetooth) with the on-board computing unit reporting a numerical value (Iqbal and Lim, 2006). Position, speed and time are continuously recorded by the GPS receiver and transmitted to the central computing unit.

Finally, Barmpounakis et al. (2016) conclude that, since a few technological obstacles that exist nowadays are overtaken, these systems can also be exploited for real time traffic monitoring. Other methods include extraction of vehicular trajectories from video recordings using a trajectory extraction system to collect vehicle traffic data (Barmpounakis et al., 2015). Although this is also not available for real time traffic monitoring it is very likely to be used for this purpose in the near future.

As shown in Table 1, the method of data transmission to the Control Centre varies and is usually based on the telematics manufacturer. Other transmission methods are via a USB cable connecting the OBD and the CC, via a GPRS/CDMA network, wirelessly from a Bluetooth device built-in the OBD or through a microSD card. The installation cost was also found to be moderate whereas the monthly/yearly fees also varied from a zero cost to $19 a month after the first year of installation.

Table 1: Manufacturers providing Telematic recording devices of driving characteristics.

Manufacturer	Data recorded: Distance, speed, time	Method of transmission	Installation cost	Monthly/yearly fee
CarChipFleetPro	Distance, time, acceleration, speed, GPS location, fuel, Engine speed	USB cable/port (customer loaded)	$149 (plus a $395 charge for software, one per fleet) Can also be used wirelessly with a $200 base unit	None
Sky-meter	time, distance, place, speed, acceleration of all driving, and the location and time of all parking	GPRS/CDMA (other protocols available at extra charge)	$50 - $250 activation fee	$5 per month plus 5%–8% of monthly premium (depending on volume)
OnStar	Distance, speed, time, (incl. other features)	Automatic through GPS S	First year free for new GM cars (only available for GM)	$18.95 per month after one year
Freematics	Speed, distance, time, location, acceleration, engine RPM	Built-in Bluetooth Low Energy and SPP module for wireless data communication or via microSD card (32GB)	99$ (Plus $30 for GPS module, plus $10 for MEMS MPU-9150 (9-axis) module, plus $10 for DUO BLE-BT 2.1 and plus 5$ for 32GB microSD)	None
Progressive (MyRate Device)	Distance, speed, time, location, acceleration, trip frequency	Wirelessly	None but $75 fee if not timely returned at end of policy	Varies

3. Driver's travel and driving behaviour risk indicators

The indicators that are recorded by each device refer to travel and driving behavioural characteristics, such as distance, time, location and speed, acceleration/deceleration, seatbelt use (www.skymetercorp.com, www.carchip.com etc.). There are a few manufacturers that measure additional information, such as the location and parking duration (www.skymetercorp.com). This information is then processed, based on rating information provided by the insurer, to generate the risk factors of interest for each driver.

Some insurers so far are charging for driving per minute or mile (or km) travelled, or modify charges based on driver's driving record, vehicle type owned, the class of road, time of the day driving, the riskiness of the historical behaviour or the riskiness of the current behaviour. Some others also charge for parking (www.skymetercorp.com) per hour parked at high risk locations (e.g., on street, in mall) but this is beyond the scope of this research.

Generally, the main driving indicators mostly used so far in literature for calculating the driving risk of an individual are shown below in Table 2:

Table 2: Risk indicators classification.

PAYD	PHYD
Total distance driven by the user (the higher the mileage the higher the risk)	Speeding expressed either as a percentage of kilometres/time driving over the speed limit or a percentage of speeding
Road network type (increased crash frequency in the cities, increased crash severity outside)	Harsh braking
Risky hours driving (increased crash frequency during a particular hours range).	Harsh acceleration
Trip frequency (a driver is more likely to cause a crash during an infrequent trip)	Harsh cornering
Vehicle type	Seatbelt use
Weather conditions	Mobile phone use

The PHYD concept is not thoroughly examined and much less implemented. Nevertheless it should be highlighted that only a handful of studies have included behavioural characteristics in their models. So far, there is only one insurance company exploiting behavioural information to assess drivers and estimate their charges (https://www.progressive.com/auto/snapshot/).

Even on a research level, there exist many indicators both for driving behaviour (harsh cornering, alcohol use, ecological driving etc.) and travel behaviour (vehicle maintenance condition, safety rating of the vehicle from the IIHS (Insurance Institute for Highway Safety)) that also affect crash risk but are not incorporated in risk modelling until now. For instance, eco-driving is a factor considered to be significantly related to crash risk (Haworth and Symmons, 2001). If fuel consumption according to the manufacturer's specifications is compared to the real consumption, conclusions can be drawn about how a user is driving (aggressive driving, speeding etc.). Moreover, the simultaneous existence of two driving characteristics, such as speeding during risky hours or braking harshly in an urban network may affect crash risk excessively. All the above should be further investigated to conclude on their significance to crash risk modelling.

However, it should be mentioned that some of these indicators e.g. alcohol use cannot be easily taken into account yet in driving behaviour models as they cannot be captured efficiently. Nevertheless, it is very likely for scientists to be able to monitor these factors in an easy and reliable manner in the near future.

4. Travel behaviour-based Insurance (PAYD)

Few studies focus on the correlation of vehicle-kilometres travelled to the hazards of traffic and therefore the determination of likelihood of a driver being involved in a crash. In the primary form of PAYD, mileage was only incorporated in the models as travel behaviour characteristic. This was derived from the fact that mileage and crash risk are close related. Indeed, there are many studies (Litman, 2005, Bordoff and Noel, 2008) that indicate a relationship between the reduction of VMT (vehicle miles travelled) and the reduction of crash risk. For example, Edlin (2003) finds that the elasticity of the number of crash esoccurring with respect to VMT is approximately 1.7 which means that if mileage was reduced by 10%, crashes would be reduced by 17%. Other researchers have found the elasticity of crash risk to be around 1.2 (ICBC Research Services Data, 1998). More specifically the authors claim that the 1981-1982 recession led to a 10% VMT and 12% insurance claims reduction in British Columbia. In support of the above, Ferreira and Minikel (2010) found that there is a high statistical significance between mileage and risk and that they are positively correlated. It should be mentioned that the above findings are based on the definition of elasticity which is the relative importance of an independent variable in terms of its influence on the dependent variable. In other words, it can be accounted for the percent change in the dependent variable caused by a 1% change in the independent variable (Washington et al., 2010).

Many researchers on the other hand, focused on the type of relationship between mileage and crashes with a number of them indicating that there are serious grounds to believe that it is neither linear nor proportional for an individual vehicle (Janke, 1991, Litman, 2008). Consequently, the number of crashes divided by the number of mileage driven for a group of users should not be expected to remain constant. Ferreira and Minikel (2010) conclude that the relationship between risk and mileage is less-than-proportional when all vehicles are considered together with class or territory differentiation and less-than-linear when these factors are not taken into consideration.

It was also found that most groups of lower mileage drivers (such as young and older drivers) tend to have higher crash rates compared to higher mileage drivers (Janke, 1991), Langford et al., 2013). As a general fact, per mile crashes tend to decrease as annual mileage increases which is attributed (Litman,

2008) to several factors such as that low mileage drivers are usually driving more miles in congested urban areas where crash risk is higher, lack of driving practice etc.

Other studies in the past presented the Pay-at-the-Pump (PATP) method which was the early stage of the mileage-based insurance policy that appeared later. Considering that fuel consumption and mileage are somehow correlated, these two methods share many similar characteristics and the same conceptual basis. PATP is the second most influential method of UBI which considers fuel consumption as its main indicator instead of mileage.

Based on the above it is clear why first studies concentrated on developing models that take into account mileage as the most (and sometimes the only) influential factor for crash risk, the mostly used of which are described below. It should be mentioned that the risk prediction increases, when mileage is incorporated along with other rating factors in the model and not alone (Litman, 1997, Ferreira and Minikel, 2010). It is shown that mileage provides a great explanatory power, when combined with space and behavioural information of the miles driven (Ferreira and Minikel, 2010). It is, thus, a powerful supplement to traditional insurance rating factors (e.g. experience and territory). This would increase fairness among motorists even more as not all drivers would be expected to pay a flat-rate premium per mile but it would be differentiated based on other driving characteristics as well.

Moreover, it has been found that, when annual mileage is taken into consideration, the influence of variables sex and education for crash prediction is minimized (Lourens et al., 1999). On the other hand, a well-documented age influence (young driver's age group) is proved and a strong positive correlation between traffic violation commitment and crash involvement (which is independent of the annual mileage driven) is seen in literature (Rajalin, 1994, Massie et al., 1997, Lourens et al., 1999).

It should be noted though that there are a few researchers like Ellison et al. (2015b) who dealt with driving behavioural models using other exposure spatiotemporal indicators as independent variables rather than mileage such as speed limits, school zones, rain, time of the day/ week, number of passengers, vehicle and driver's demographic characteristics.

4.1 Pay-at-the-Pump (PATP)

As for the PATP method, Wenzel (1995) argued why insurance premiums should be estimated based on use. Claiming that VMT is a good predictor of crash costs, he proposed a travel behaviour -based system which was actually a per-gallon surcharge for consumers, a method similar to the PATP method. Wenzel also suggested that premiums should be the sum of a fixed amount based on location, vehicle safety characteristics and driving record, most of which are travel behaviour characteristics, plus a variable amount based on fuel consumption (per-gallon surcharge).

In other forms of PATP (Sugarman, 1994), the foundation of a governmental or county organization is introduced that will collect the funds at the pump in the form of fuel surcharges. Sugarman suggested that apart from the fuel surcharge, additional charges should be imposed based on drivers' driving record and experience as well as on vehicle ownership. The latter amount was proposed to be defrayed either as a once-off fee or as an annual instalment. It should be highlighted that this method would substitute lawsuit system or tort liability only for bodily injuries and not for material damages. The author concludes that this new system will provide fairer funding, greater safety and better compensation for most users. On top of the benefits presented above by Litman (2004), Sugarman (1994) claimed that the new vehicle injury plan (VIP) would assist in overcoming many problems that appear in today's insurance policy such as the fact that a large percentage of premiums goes to claims administration, duplicate other sources of compensation, for pain and suffering rewards or is lost to fraud, the enormous number of seriously injured victims that are vastly undercompensated, , the unsatisfying claims process the long payment delays of many bodily injury claims and finally the fact that safer driving and safer vehicles are insufficiently encouraged.

Khazzoom (2000) calculated the marginal travel behaviour risk of the average driver to be around 2c/mile and suggested that the fuel surcharge could be set to 50c/gallon. He also argued for PATP over VMT-based insurance stating that the latter does not remove uninsured motorists from the road or encourage them to switch to more fuel efficient vehicles burdening this way the environment as well as it does not have any implementation problems.

Generally, research indicates that PATP results to welfare benefits with both a direct and an indirect manner (Kavalec and Woods, 1999, Khazzoom, 1999, Khazzoom, 2000). An average driver can be benefitted either individually by paying lower insurance premiums and have enhanced road safety or indirectly by societal benefits such as reduced external costs such as reduced energy consumption, congestion, greenhouse gases, emissions etc.

However, due to the drawbacks of the PATP method referred below, PATP was not extensively implemented. Kavalec and Woods (1999) claimed that introducing a surcharge for gasoline is an incentive for consumers to drive vehicles that are more energy efficient in order to reduce their exposure to tax and not reduce their annual mileage significantly. Khazzoom (2000) raised the issue that differences in vehicle fuel efficiency are probably leading to a discrepancy between drivers which is nevertheless fairer than today's lump sum policy. According to the author, PATP might also cause a slight shift to energy efficient vehicles, a fact that will increase the above mentioned discrepancy. Previously (Khazzoom, 1999), criticism against PATP was classified into two categories i.e. criticism of PATP design such as state bureaucracy, uncertainty of insurers' income and long-distance motorists penalization and the consequences of adopting this new method such as the burden on lower income insurers and the shift to fuel efficient vehicles.

4.2 Mileage-based Insurance

Because of the drawbacks of the PATP method, efforts were focused on distance-based methods that are directly "penalizing" driving. For example, Weaver (1970) examined the potential of paying premiums proportionally to vehicle use (pay-as-you-drive - PAYD) as a possible solution for the economic asymmetry that currently exists in the vehicle insurance market. Survey results indicated that the new insurance method would reduce transaction costs, lead to more cost-efficient consumer behaviour, reduce premiums and benefit insurance companies, allowing them to create policies that better represent actual risk corresponding to each consumer. Other social benefits of PAYD insurance were also examined as well as the obstacles to the development of such a policy is likely to result from the implementation of such a program such as reducing GHG emissions and CO2, dependence on oil, lowest number of crashes, the reduced need for maintenance of the infrastructure etc.

Texas Mileage Study published by Progressive Insurance (Progressive Insurance, 2005), which is a PAYD provider in the US, was outstanding in terms of the number of observed vehicles and the observation period (the experiment lasted 36 Months and 203,941 Vehicles insured by Progressive Casualty Insurance Company participated; although the authors also do not provide a detailed description of their sample selection). In the final report of this study (Progressive Insurance, 2005), the relationship between annual mileages and incurred insurance losses for different coverage types is presented using a regression analysis methodology. In other words, it was shown that the dependent variable (insurance claims) is strongly influenced by the number of vehicle-miles travelled by the user. The basic model tested was a linear regression model, achieving an R^2 (goodness-of-fit indicator) of > 0.82. Apart from annual mileage, no more variables were tested for correlation with insurance claims within this study.

Bordoff and Noel (2008) developed and evaluated a mileage-based model (PAYD) resulting that each household can reduce up to $ 270 per vehicle insurance contributions to be paid. The authors pointed out that if users were charged per kilometre, they would have an extra incentive to drive less, which would result in crashes reduction. They also consider that the reduction of vehicle would be around 8%, a figure which is equivalent to $ 50-60 million due to reduced harmful effects on driving. The above reduction would also reduce carbon dioxide emissions by 2% and oil consumption by about 4%. Nichols and Kockelman (2014) showed that the average vehicle will be driven less by 2.7% (237 mileage reduction per year), with benefits for average consumers only $ 2.00 per vehicle with a premium that is partly fixed and partly based on mileage. Drivers with lower vehicle kilometres per year are expected to receive the greatest social benefits, thanks to the convex relationship between vehicle mileage and crash probability. This analysis supports the findings of the existing literature, namely that the PAYD policy can reduce vehicle kilometres travelled annually and leads to a fairer premiums system.

Examples of the above mentioned PAYD models in practice are National General (http://www.nationalgeneral.com/auto-insurance/smart-discounts/low-mileage-discount.asp) which is providing a discount of up to 54% and Metromile (https://www.metromile.com/insurance/) Insurance companies which charging 3.2¢ per mile.

5. Behaviour-based Insurance (PHYD)

Current Pay-As-You-Drive systems are said to have many weaknesses and shortcomings, because they are focused only on the number of driven kilometres and not on driving behaviour (Kantor and Stárek, 2014). Evaluating how a user is driving is most times more crucial to crash risk estimation than counting how much he is being driving. Modelling the driving pattern of each driver efficiently is a matter of significant importance for crash risk modelling, as it gives the opportunity not only to sufficiently understand differences between driving behaviours but take them into consideration as well.

Most researchers used a linear modelling approach to model PHYD insurance (Iqbal and Lim, 2006, Boquete et al., 2010). For instance, Boquete et al. (2010) implemented a UBI model that takes into account driving behaviour attributes. The on-board system was installed in vehicles and data were transmitted using mobile data service to the control Centre. The basic concept was to build a premium cost model based on how much (mileage), where (Zones used), when (Day/night) and how (overspeeding, harsh accelerations, number of vehicle passengers, mobile phone use) a vehicle is driven. Premiums were calculated as a sum of a fixed charge imposed to each driver plus a linear combination of the above mentioned indicators and their coefficients. In other recent studies (Iqbal and Lim, 2006) driving behavioural attributes are also included in cost calculation and apart from exposure characteristics such as weather and light conditions risk, rush hour risk and road network risk terms, they also incorporate speeding risk terms which stands for the percentage of driving over the speed limit after detecting the road network type the driver is using. Premium cost in this study was computed as the product of a base rate for each driver by all risk factors calculated for each indicator (road network type, overspeeding etc.) (Iqbal and Lim, 2006).

On the other hand, there have been studies where the alternative method proposed is a fuzzy-linguistic approximation apparatus which according to the authors is a suitable tool taking into consideration the insufficient exact knowledge and the large possible combinations of the parameters used as model's input (Kantor and Stárek, 2014). A concise algorithmic procedure successfully incorporated the process of the driving pattern assessment and a projection of that evaluation into the insurance premium was produced. The algorithm consisted of six algorithmic steps namely data collection, meteorological conditions evaluation, vehicle dynamic qualities determination, manoeuvre type determination, manoeuvre style evaluation and finally number of penalty points assignment and determination of driving style sanctions. As for the types of manoeuvres, driving straight, turning, overtaking, speeding, aggressive deceleration, non-fluent driving (frequent acceleration and deceleration) were taken into account but the manoeuvre style is being evaluated for driving straight, turning, overtaking and aggressive braking. Finally, the parameters used as input for the fuzzy model were visibility, deteriorated road conditions, sufficient vehicle performance, acceleration in x and y axes, speeding, motorways and roads (directions separated or not separated). Using smartphones as measurement probes Handel et al. (2014) also followed an algorithmic procedure to form the scoring procedure describing the risk profile based on the figure of merits of actuarial relevance. Parameters used in this research include speeding, road network type, risky and rush hours driving, harsh acceleration, harsh braking, harsh cornering, manoeuvre type, trip duration, energy consumption, trip distance and smoothness.

Chowdhury et al. (2014) applied a statistical analysis and algorithmic approach to calculate driving score and proved that these two methods are able to capture the relationship between Jerk energy (change rate of acceleration in m/s3) and speed. Based on this relationship, a scoring mechanism for monitoring a vehicle was successfully established through large scale data collection of large number of vehicle made possible by OBD devices and the smartphone. Authors concluded that this algorithm can serve either as service analytics or for PHYD insurance model premium calculation.

There are also studies in literature where more than one methods were tested to find the one that fits best. Paefgen et al. (2013) demonstrated the potential of high-resolution travel behaviour data for PAYD insurance pricing by training and testing the applicability of three different approaches, compare logistic regression, neural network, and decision tree classifiers and comparing their outcomes. The predictor variables found to be significant in this study were speeding, road network, risky and rush hours, mileage and day of the week with vehicle mileage to be the strongest single predictor variable; the authors highlighted that its predictive power was further improved, particularly for logistic regression, by applying a logarithmic transformation. Paefgen et al. (2014) exploited PAYD insurance data from 1600 vehicles obtained from an insurance provider and based on data recorded by the in-vehicle data recorders (IVDR) the authors developed and validated a variety of models in order to investigate and explain the existing differences between vehicles that get involved in crashes and those that do not. This research employed logistic regression modelling techniques to estimate the probability of incident occurrence. It was shown that crash risk fluctuates throughout the day (lower for the daytime interval and higher for nightfall), the week (lower risk on Friday and weekends), road network type (driving on urban roads is correlated with high risk) and velocity range (mid-range (60 - 90 km/hr) velocities are associated with lower risk compared to low-range (0 - 30 km/hr) and higher range(90 – 120 km/h)).

A variation of PHYD named Pay-As-You-Speed was tested by Hultkrantz & Lindberg (2011) who simulated an insurance scheme based only on speeding indicator. The experiment lasted two months and participants that took part were divided in two groups; those that were receiving a malus/bonus for their speeding behaviour and those who were only being monitored. Each participant of the first group received a fixed monthly payment which was deducted every time the participant was violating speeding traffic rules. Results indicated that severe speeding violations were reduced during the first month but, after participants received their feedback reports with an account of earned payments, those not given a penalty did not change their behaviour in the second month. According to performed research on PHYD schemes so far, this new method presents many potentials and appears to have many benefits. However, although PHYD is undoubtedly the best way to rate a user's driving and estimate his/her crash risk, it still remains a sharp shift from today's lump sum policy; an alteration that probably needs some effort in order to be adopted by society. Moreover, PAYD methodologies implemented so far seems to be very persistent and unilateral as to the parameters considered. With regards to travel behaviour - based modelling, mileage is not the only factor influencing crash risk and therefore multivariate travel behaviour -based insurance models should be developed taking into account parameters such as the road network used, time-of-the-day driving etc. (on the top of mileage driven).

Examples of the above mentioned PHYD models in practice are Progressive (https://www.progressive.com/auto/snapshot/) and Allstate (https://www.allstate.com/drive-wise.aspx) insurance companies which promise safe drivers a discount of up to 45% on car insurance based on a safe driving style features such as harsh braking, speeding and when the user is driving.

Table 3 summarizes all literature collected and presented in this review. For each Usage-Based Insurance model implemented thus far, the type of the model as well as the safety indicators used are illustrated. The first ten models presented in Table 3 are PAYD models as they incorporate only travel behaviour parameters such as mileage and fuel consumption while the last seven models are PHYD models as they use behavioural indicators such as speeding, harsh braking etc.

Table 3: Usage-Based Insurance model Literature

Reference	Model Type	Speeding	Road Network	Risky hours	Rush hours	Harsh acceleration	Mileage	Harsh braking	Manoeuvre	Harsh Cornering	Day of the week	Visibility	Territory	Vehicle type	Passengers	Trip duration	Weather	Smoothness	Trip distance	Jerk Energy	Mobile phone use	Energy consumption	Fuel	Gender	Class
Khazzoom (2000)	Linear																						√		
Progressive Insurance (2005)	Linear						√																		
Bordoff & Noel (2008)	Linear						√																		
Ferreira & Minikel (2010)	Non-Linear (Poisson)						√																		
Ferreira & Minikel (2010)	Linear						√																		
Buxbaum (2006)	Linear						√																		
Zantema et al. (2008)	Linear						√																		
Litman (2005)	Linear						√																		
Ferreira & Minikel (2010)	Non-Linear (Poisson)						√																	√	√
Ferreira & Minikel (2010)	Linear																							√	√
Ferreira & Minikel (2010)	Linear						√																	√	√
Kantor & Stárek (2014)	Non-Linear (algorithm)		√	√	√		√																		
Iqbal & Lim (2006)	Non-Linear	√	√		√							√					√								
Boquete et al. (2010)	Non-Linear	√		√		√	√						√		√						√				
Handel et al. (2014)	Non-Linear (algorithm)	√	√	√	√	√		√	√	√						√		√	√			√			
Paefgen et al. (2013)	Non-Linear	√	√	√	√		√				√														
Paefgen et al. (2014)	Generalized Linear/ Non- Linear	√	√	√	√		√				√														
Chowdhury et al .(2014)	Non-Linear																			√					
Hultkrantz & Lindberg (2011)	Non-Linear	√																							

6. Critical Synthesis

The aim of studying UBI is the development of a premium calculation system based on the travel and/or driving behavioural characteristics during driving and ultimately to create reliable models able to associate driving risk with travel behaviour (for PAYD models) and/or driving behaviour (for PHYD models) and charge road users based on that risk. PAYD premium calculation method is based only on travel behaviour characteristics. Risk is only correlated with vehicle's exposure, assuming that the probability of a crash occurrence increases as some indicators referred below, such as driven kilometres, increase. As illustrated in figure 1, traditional insurance approach does not consider the exposure of a vehicle or the behaviour of a user and assigns to a specific vehicle and driver an "average premium" that corresponds to the "average driver" and consequently to an "average crash probability". On the other hand, PHYD is based on users driving behaviour evaluation and travel behaviour leading to a realistic estimation of the corresponding risk. The PHYD model incorporates a large number of parameters allowing the accurate estimation of the driving risk. The final outcome of the PHYD model can be an individual risk indicator that will depict the risk associated with the driving behaviour of a user. Since premium calculation in PHYD is based on the evaluation of driving behaviour of the user, it leads to a more realistic assessment of the risk than PAYD approach does.

During the last few decades traditional motor insurance has started to gradually transform into Usage-Based Insurance. There remains the question though, to what extent is this new type of motor insurance going to be widely adopted and which indicators will be fully incorporated? In the authors' opinion, UBI will play a key role in motor insurance market in the future and as a result it will strongly influence traffic safety in total. Figure 1 illustrates the types of insurance that currently exist in the marketplace as well as the intuition of the authors on how motor insurance future will be formed. Since the trend in innovative motor insurance revealed above is to implement schemes that progressively incorporate travel and behavioural factors the authors consider that future models will be in the form of Pay-As-How-You-Drive (PAHYD) including parameters from both PAYD and PHYD models.

It is evident that the PAYD model is a more simplistic approach using fewer parameters as risk indicators. However, it has also significant advantages since (a) it is easier to implement (b) the period for the development and the verification of the model is significantly smaller, as less data are required and, also, significant information may be found in literature and reports of relevant organizations (c) it is targeted to the vehicles that are not often used. On the other hand, PHYD is a more sophisticated approach aiming to (a) associate the driving risk with a large number of indicators quantifying - in a realistic manner- the driving behaviour (b) raise driving awareness and motivate the driver to evaluate and improve their own driving behaviour and (c) increase the profit of the Insurance Companies via this self-improvement of the drivers.

Ranking insurance pricing schemes based on how well marginal vehicle costs are represented by different fees (Litman, 1999), models taking into account time and location information (PHYD) were the best performing, followed by mileage-based models (PAYD), PATP models (PAYD), fixed vehicle charges models (current insurance policy) and external costs (not charged to drivers) models respectively.

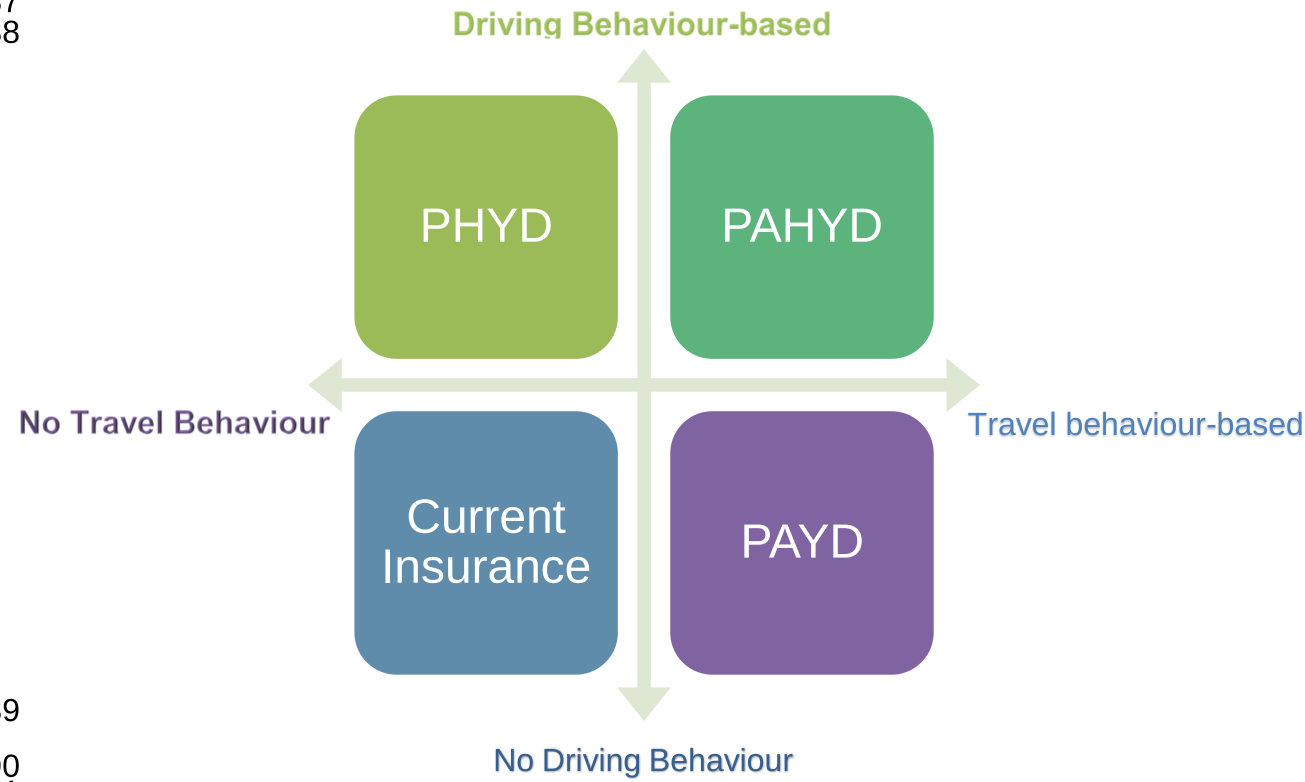

Figure 1: UBI and current Insurance policies

Finally, as shown above, although the contribution of past research on PAYD pricing is important, only a small percentage to date has dealt with PHYD systems. As previously mentioned, this method objectively calculates crash risk since it takes into account several important factors such as sudden braking / acceleration, driving over the speed limits, etc. which makes it a more reliable tool for calculating the probability of crash involvement. This is where future research should mainly focus on as well as on developing and evaluating PAYD and PHYD models and compare their efficiency.

In terms of the indicators exploited so far in PAYD/ PHYD literature, it should be mentioned that there are a few such as alcohol use, vehicle maintenance condition, vehicle safety rating etc. that affect crash risk and are not yet included in UBI modelling. Furthermore, the effect of two different driving characteristics such as harsh acceleration on a highway should also be examined. Although some of these factors cannot be currently monitored in an easy and reliable manner, most of these can or will be able to be efficiently captured in the near future.

The above literature review reveals a trend in PAYD schemes, which are mainly focusing on the effects, externalities and potentials that UBI offers. Although the potential that arises from the implementation of PAYD schemes both on insurance companies and drivers has been examined thoroughly (Husnjak et al., 2015), PHYD appears not to be exhaustively modelled till now.

Moreover, all metrics used in UBI modelling are proved to be very helpful in describing and representing a driver's behavior. Apart from these metrics though, a few more factors should be also considered such as mobile phone and seatbelt (recorded from the OBD) usage, reaction time, time to collision (from naturalistic driving experiments) etc.

7. Discussion

This paper constitutes a systematic effort to gather, group and present the most scientifically strong studies in literature relevant to UBI approaches mainly focused on PAYD and PHYD methodologies. Unlike the past, there is an obvious trend for motorized insurance to become even more personalized. As a result, instead of calculating insurance premiums based only on demographic characteristics such as age, number of years holding a driving licence etc., personal driving characteristics either travel and/or driving behavioural are slowly incorporated into insurance models.

As seen from the above literature review there has been an extensive effort of analysis and evaluation of PAYD methods. The small extent of implementation thus far has demonstrated that it has a great influence on all levels, economic, social, environmental, etc. This is a ground-breaking first attempt to change the established insurance billing system that is currently anachronistic and unfair to many users and also proved not to contribute in any way in crash reduction which is the goal of road safety.

In the future, a gradual global transition towards PAYD/PHYD insurance could be envisaged. Low-risk drivers (low-mileage, less risky drivers etc.) will receive gain many incentives to opt out of traditional insurance in favour of alternative insurance policies such as mileage-based insurance (Parry, 2004); this is becoming increasingly feasible as telematics systems are gradually incorporated in newer vehicles. Governments are also likely to encourage this trend in the future through policies and political decisions such as subsidies, tax waivers for insurance companies offering alternative policies like these.

Annual crash risk can be calculated as the product of per-mile crash risk times annual mileage (Litman, 2008). Although imposing drivers to reduce their annual mileage would probably lead to reduced crash risk, two factors are not taken into consideration. Firstly, a driver that is penalized based only on mileage is not incentivized at all for improving his/her driving behaviour. Therefore, per-mile risk remains an unspecified factor which can fluctuate over time which means that despite the fact that mileage is reducing, total crash risk can still be increased. Secondly, insurance system still remains unfair and the cross-subsidies phenomenon is not eliminated since per-mile crash risk is considered to be the same for all drivers and is not individually calculated. Consequently, behavioural aspects of driving should be incorporated in insurance models in order to contribute towards current trends of personalized vehicle insurance.

In support of the above, even if it is assumed that per-mile crash risk remains constant, while annual mileage is reducing throughout the year, total individual crash risk reduction cannot be calculated since it depends on other behavioural characteristics that are not currently recorded and therefore not taken into consideration in today’s usage-based insurance. Driving information such as number of harsh brakings and accelerations, percentage of overspeeding, road network category etc. should be included in driver’s evaluation so as a per-mile risk factor could be assigned to each individual driver. In other words, risk factor is risk’s increase rate which indicates how total individual risk is increased as mileage raises. Calculating this factor is the only way to accurately predict individual crash risk and consequently, fairly charge each driver based on the risk he reflects. Since technological solutions can be given nowadays and conditions to efficiently record and manage real-time big data are finally met, science should move towards that direction.

Based on the review conducted in this paper to address the research questions raised in the introduction, the authors conclude that Usage-Based Insurance is expected to improve traffic safety in total as most UBI models (Paefgen et al., 2014) focus on determining the relationship between road safety parameters, such as crash risk, and behavioural indicators such as mileage, risky hours, harsh braking/ acceleration etc. This can be implemented by classifying each driving style on a continuous scale from low to high risk (Sagberg et al., 2015) and subsequently estimate the safety scoring for each driver. It was also observed that most researchers make use of in-vehicle data recorders (IVDR) such as On-Board-Diagnostics (OBD) devices and smartphones to collect and transmit driving data to the central databases. Because of smartphones’ high penetration rates in households as well as of the high hardware cost of IVDR, it is strongly believed that smartphones will be mainly used for data acquisition in the future.

In terms of the indicators mostly used in today’s UBI models, mileage, speeding, road network type and risky and rush hours driving predominate among them. Apart from these though, it is anticipated that more behavioural parameters e.g. harsh braking/ acceleration/ cornering, mobile phone use etc. will be increasingly used in future models because of the fact that they seem to be more representative of crash probability. Despite the fact that most barriers for the wide diffusion of UBI schemes have been overtaken, there exist still a few such as the relatively medium-level capability of cloud computing services in order to analyse and exploit big-databases and the problems in quality of the data originating from the devices mentioned above. In the authors’ opinion, future UBI will be transformed in such a way as to adopt parameters from both PAYD and PHYD insurance schemes establishing a new Pay-As-How-You-Drive (PAHYD) model with both travel behavioural and driving behavioural parameters.

Regarding future directions and as for driver’s individual safety scoring, since it is possible to classify each driving style on a continuum scale from low to high risk, future research should focus on actual crash involvement data exploitation. Data collection and analysis techniques from naturalistic driving experiments are expected to play a significant role in the future. In naturalistic driving experiments where the user drives and reacts as usual, it is most likely to “capture” those driving habits, styles and indicators exploiting normal driving data recorded and associate these with real crashes. This could be proved extremely convenient for researchers especially if there exist datasets including both crash-involved and crash-free data that could be linked to driving behaviour indicators and/or styles. As revealed by the review, using smartphone technology in the framework of naturalistic driving experiments is an innovative cost-effective approach for gathering and transmitting large amounts of travel and behavioural data. This methodology is now being spread and will be extensively used in future UBI research.

In terms of the indicators usually incorporated in UBI models there are many that should also be taken into consideration in future research as they influence the most traffic crashes and related insurance claims. As past review has highlighted (Sagberg et al., 2015), crash involvement is so far predicted mainly by speeding and a high frequency of driving-related violations, probably because these are typical characteristics of aggressive and/or impatient driving. Driver drowsiness and distraction (Kaplan et al., 2015) are two factors that influence the most traffic crashes and related insurance claims and along with other such as alcohol use, ecological driving and vehicle maintenance condition should also be taken into account when modelling for Usage-Based Insurance.

From a road safety perspective, eliminating the cross-subsidies phenomenon would reward good drivers for driving safely. It would also provide a strong motivation for risky drivers to improve their driving behaviour, differentiate their travel behaviour and reduce their degree of exposure by being charged higher insurance premiums and receiving feedback and monitoring their driving performance and preferences. As a result, an insurance model incorporating individual driving characteristics would enhance safety by reducing crash risk both totally and individually since it would provide drivers with both positive and negative incentives to alter their travel behaviour and improve their driving behaviour. All the above suggest that there exist numerous and important challenges emerging on this research field which will be further investigated in the near future.

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