Willingness-to-Pay for Usage-Based Motor Insurance

Athanasios Theofilatos, PhD (Corresponding Author)
Research Associate
National Technical University of Athens,
5 Iroon Polytechniou St., GR-15773, Athens, Greece
Tel: +30 210 772 1575; Fax: +30 210 772 1454
E-mail: atheofil@central.ntua.gr

Dimitrios I. Tselentis
Research Associate
National Technical University of Athens,
5 Iroon Polytechniou St., GR-15773, Athens, Greece
Tel: +30 210 772 1575; Fax: +30 210 772 1454
E-mail: dtsel@central.ntua.gr

George Yannis, PhD
Professor
National Technical University of Athens
Department of Transportation Planning and Engineering
5 Iroon Polytechniou St., GR-15773, Athens, Greece
Tel: +302107721326, Fax: +302107721454
E-mail: geyannis@central.ntua.gr

Manos Konstantinopoulos
National Technical University of Athens
Department of Transportation Planning and Engineering
E-mail: manoskonstantinopoulos@yahoo.gr

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ABSTRACT

This paper aims to investigate which parameters affect users' willingness to pay for alternative usage-based motor insurance pricing schemes such as Pay-as-you-drive (PAYD) and Pay-as-how-you-drive (PHYD). For that reason, a dedicated questionnaire was designed and administered to 100 participants including both revealed and stated preference questions and proposed scenarios regarding current and alternative insurance schemes. Then a mixed logit model was applied to examine the effect of driving characteristics, drivers' demographics and the price of vehicle insurance premiums on vehicle insurance choice. Two distinct mixed logit models were developed; one mixed logit model to investigate the factors influencing the choice of present insurance policy over PAYD and one for present insurance policy over PHYD. Results indicated that women and smartphone owners are more likely to choose a new insurance schemes. Kilometers and cost reduction were also found to affect similarly the choice for both Usage-Based-Motor Insurance (UBI.) Moreover, the higher the speed reduction imposed to the user, the lower the probability of the UBI scheme to choose it. It was also found that people over 40 years old are less likely to choose PHYD insurance. Lastly, people with lower education are more likely to choose PAYD insurance.

INTRODUCTION

Usage-based motor insurance (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 concept is that drivers pay insurance premiums based on their travel and driving behavior instead of a fixed price based on demographics and/or their driving experience only. 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 (1).

Insurance charging systems based on travel behaviour are often called Pay-As-You-Drive (PAYD) Usage-Based Insurance schemes. Driver's travel behaviour can be defined 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. On the other hand, Insurance charging systems based on Driving Behaviour are often called Pay How You Drive (PHUD) Usage Based Insurance schemes. Driving behaviour can be defined 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 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.

For the estimation of insurance premiums, the "Willingness to Pay" (WtP) methodology is examined, which is in fact the reflection of the individual estimate on how much money an individual is willing to pay (or sacrifice) to obtain certain benefits or avoid costs (2). Apart from the opinion of the individual on the desired goods or services value in comparison to other desirable objects, the amount specified by the respondent also reflects the ability of people to pay. Individuals can judge their own wealth and therefore, values and estimates derive from an oriented domination of the consumer. The existing income or wealth distribution is considered acceptable if the amount resulting from the WtP will be adjusted by the individual's ability to pay (3).

When analyzing stated preferences in discrete choice situations, one common way is to apply mixed logit models (4). One reason for choosing this type of models is to account for unobserved heterogeneity and variations among observations. It is therefore important to apply a methodology that allows for the possibility that the influence of variables affecting users' preferences may vary across the sample. This is an important consideration because relatively recent research carried out by Brownstone and Train (5), Train (6, 7), Revelt and Train (8, 9), McFadden and Train (10), Bhat (11), has demonstrated the effectiveness of the mixed logit model that can explicitly account for such variations. It is noted that due to the effectiveness of the mixed logit model, it is also widely applied in other fields of transport, as for example in road safety (12, 13).

Consequently, this paper aims to identify the parameters that affect users' willingness to pay for usage-based motor insurance, proposing alternative pricing methods such as PAYD and PHYD. A mixed logit model is implemented to investigate and better understand the effect of driving characteristics (driving style and driving needs), drivers' demographics (gender, age, marital status, income, etc.) and the price of vehicle insurance premiums on vehicle insurance choice.

DATA

In order to identify users' preferences and the criteria influencing their choice, the two methods were evaluated by respondents using multiple choice and scaled questions. For most questions, a five levels scale was used (1-5) in which the significance of individual factors was evaluated as 1 = "not at all" to 5 = "very".

The questionnaire was designed including both revealed preference questions about current vehicle and insurance type etc. and stated preference scenarios related to current and alternative insurance schemes. To increase the number of alternative tested scenarios, two different tabs were designed with four PAYD and eight scenarios PHYD each and each of the 100 respondents answered a single tab. The questionnaire is structured in 4 sections and questions included:

• general respondent's driving data (years since license was obtained, vehicle make, current insurance cost etc.),
• driving behavior data
• alternative stated preference scenarios about the new insurance premium policies (PAYD and PHYD) and their benefits
• personal - demographic data to draw conclusions about the sample characteristics.

The required time for completion was 10-12 minutes and it was administered to drivers being stopped at a motorist's service station in Attica.

As for the number of scenarios chosen, it was decided that for the proper implementation of the research the number of scenarios should be reduced. Based on the number of possible values that the variables of the stated preference questionnaire were designed to take, the number of different scenarios results to 16 for PAYD and 80 for PHYD. The number of different combinations in this study was reduced based on an orthogonal design that was implemented under the assumption that no correlations between typical alternatives exist. Occasionally, in stated preference surveys fractional factorial design can be used instead of full factorial design. Both these designs ensure orthogonality however, the full factorial design would include 16 out of 80 scenarios respectively, in contrast to the fractional comprising (usually much) fewer combinations and are guaranteed to meet some desirable statistical properties such as the identification and accuracy (1).

Table 1 summarizes all alternative specific variables used in different scenarios used both for present insurance and the two new insurance schemes, PAYD and PHYD. Present insurance's values were chosen to be zero to facilitate the respondent by not being affected by changes both in new and present insurance schemes.

It should be highlighted that individual variables are defined as all variables that characterize each individual such as age, gender, education etc. whereas alternative variables are those variables that are used in stated preference questionnaire to test how a respondent's choice varies while their values are fluctuating.

TABLE 1 Descriptive Statistics for Alternative Specific Variables

ALTERNATIVE SPECIFIC VARIABLES	Abbreviation	Mean	St.deviation	Min.	Max.
PRESENT INSURANCE					
% change in mileage (current Insurance)	KM	0.00	0.00	0.00	0.00
% change in Insurance Cost (current Insurance)	COST	0.00	0.00	0.00	0.00
% change in Speed (current Insurance)	SPEED	0.00	0.00	0.00	0.00
PAYD INSURANCE					
% change in mileage (PAYD Insurance)	KM	-11.76	6.58	-20.00	-5.00
% change in Insurance Cost (PAYD Insurance)	COST	-11.69	6.63	-20.00	-5.00
PHYD INSURANCE					
% change in mileage (PHYD Insurance)	KM	-6.25	9.61	-20	5
% change in Insurance Cost (PHYD Insurance)	COST	-11.43	6.78	-20.00	-5.00
% change in Speed (PHYD Insurance)	SPEED	-11.47	6.80	-20.00	-5.00

Regarding the sample characteristics, 100 respondents participated in the survey of which 45% were women, 53% married, 98% makes use of a PC and 78% is a smartphone owner. All individual specific variables tested in models developed are summarized in Table 2 along with their abbreviation and a few descriptive statistics such as mean, standard deviation, min and max values. The most important highlights are that:

• The majority of respondents were between 30-50 years old. That is also illustrated in figure 1 where it is shown how gender is distributed by age category. As it appears, 43% and 28% belong to the age category of 30-40 and 40-50 respectively.
• Most respondents' income was between 10,000 and 25,000 Euros.
• 45% was working in the public sector whereas 40% in private sector.
• 72% had pursued a degree after school.

In order to apply the mixed logit model, data had to be appropriately handled and some transformations took place. For that reason, the alternative specific variables (X11, X12, X21, X22, X13, X23) were recoded as "Km", "Cost" and "Speed" respectively.

TABLE 2 Descriptive Statistics for Individual Specific Variables

INDIVIDUAL SPECIFIC VARIABLES	Abbreviation	Mean	St.deviation	Min.	Max.
Gender = Female	GENDER_F	0.45	0.50	0.00	1.00
Age: 18-25 (reference category)	AGE1	0.04	0.20	0.00	1.00
Age: 25-30	AGE2	0.07	0.26	0.00	1.00
Age: 30--40	AGE3	0.43	0.50	0.00	1.00
Age: 40-50	AGE4	0.28	0.45	0.00	1.00
Age: >50	AGE5	0.11	0.31	0.00	1.00
PC usage is made	USAGE_PC	0.98	0.14	0.00	1.00
Smartphone Owner	SMARTPHONE	0.78	0.41	0.00	1.00
Married	MARRIED	0.53	0.50	0.00	1.00
Income <10000 (reference category)	INCOME1	0.06	0.24	0.00	1.00
10000 < Income < 25000	INCOME2	0.54	0.50	0.00	1.00
Income > 25000	INCOME3	0.40	0.49	0.00	1.00
Occupation: Public Sector	OCCU1	0.45	0.50	0.00	1.00
Occupation: Private Sector	OCCU2	0.24	0.43	0.00	1.00
Occupation: University Student	OCCU3	0.03	0.17	0.00	1.00
Occupation: Freelancer	OCCU4	0.09	0.29	0.00	1.00
Occupation: Enterpreneur	OCCU5	0.03	0.17	0.00	1.00
Occupation: Household	OCCU6	0.02	0.14	0.00	1.00
Occupation: Technician	OCCU7	0.00	0.00	0.00	0.00
Occupation: Pensioner (reference category)	OCCU8	0.07	0.26	0.00	1.00
Occupation: Unemployed	OCCU9	0.02	0.14	0.00	1.00
Occupation: Other	OCCU10	0.05	0.22	0.00	1.00
Education: Primary Education	EDU1	0.03	0.17	0.00	1.00
Education: Secondary Education (reference category)	EDU2	0.24	0.43	0.00	1.00
Education:Technological Educational Institute	EDU3	0.34	0.17	0.00	1.00
Education: University Degree	EDU4	0.11	0.31	0.00	1.00
Education: Postgraduate Degree	EDU5	0.24	0.43	0.00	1.00
Education: Ph.D.	EDU6	0.03	0.17	0.00	1.00
Education: Other	EDU7	0.03	0.17	0.00	1.00

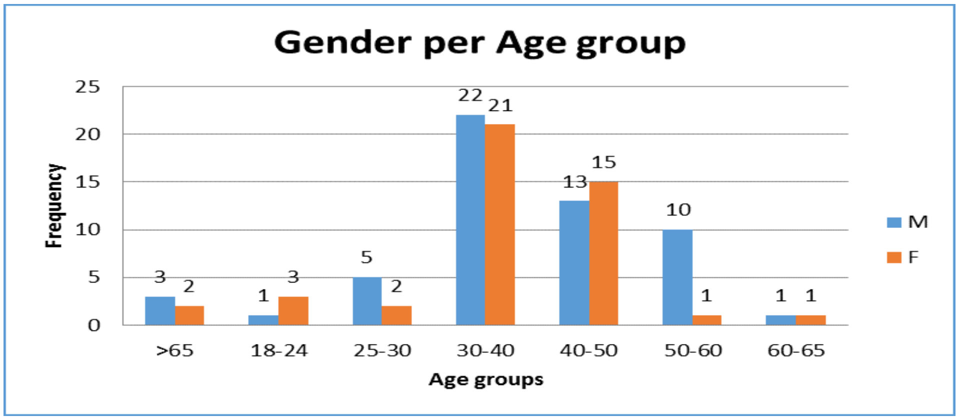

FIGURE 1 Gender distribution per age group.

As for the preference on new motor insurance schemes as it appears in figure 2 and 3, the majority of the respondents would be willing to switch to a new insurance policy. More specifically, in all education categories people seem to prefer a transition to UBI except from people with secondary education. The same applies to all age categories except from people between 50-60 years old, who answered that they would not switch to a usage-based insurance scheme. These two findings probably indicate a conservative attitude towards new insurance policies from older and lower education level people.

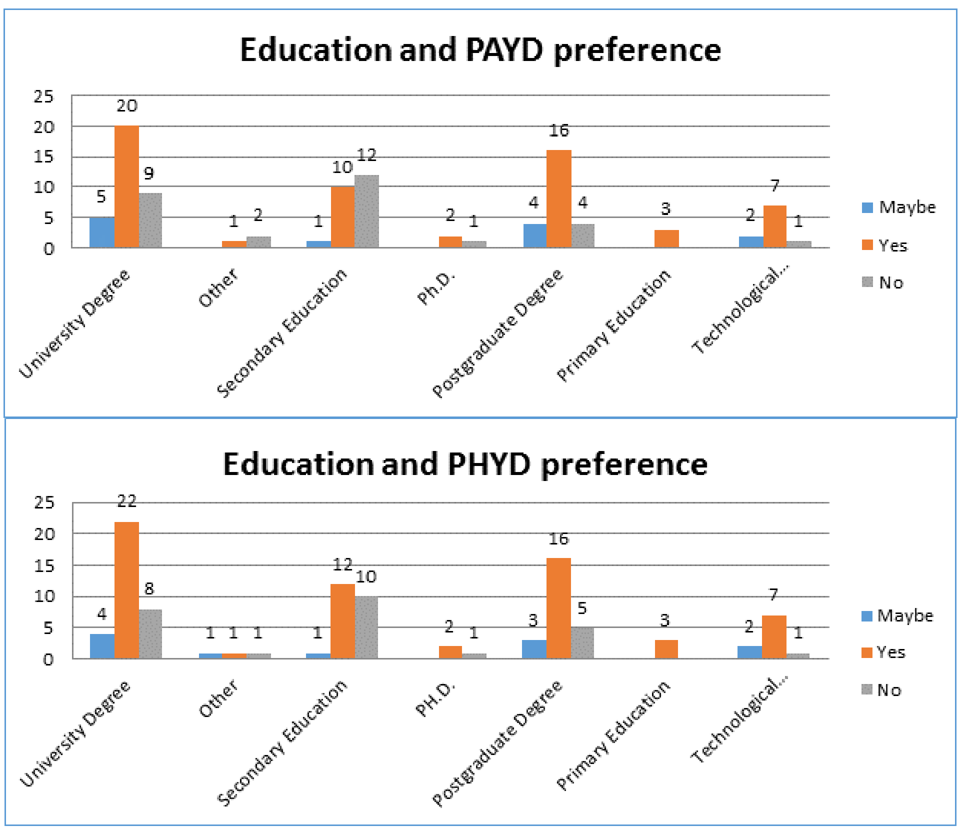

FIGURE 2 PAYD and PHYD preference distribution per education group.

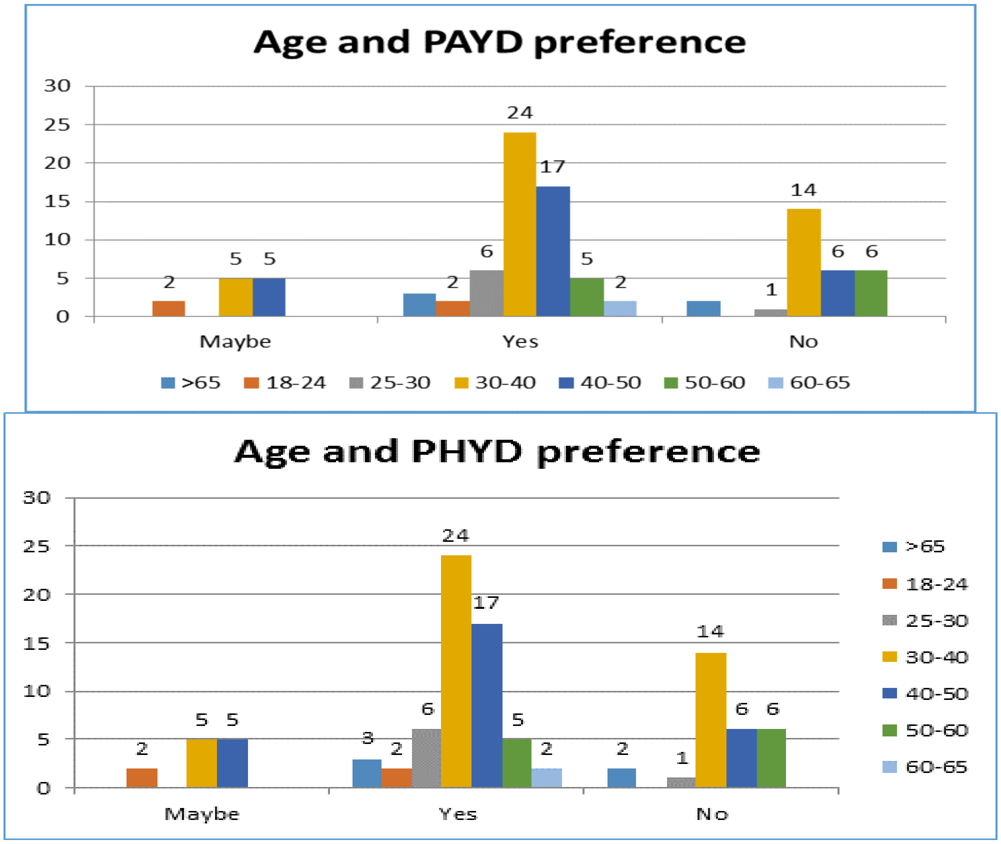

FIGURE 3 PAYD and PHYD preference distribution per age group.

METHODOLOGY

Mixed Logit Models

The proposed methodology to analyze the stated preference questionnaire regarding Pay As You Drive (PAYD) and Pay How You Drive (PHYD) is the mixed logit model (random parameter binary logistic model). Since the alternatives for each insurance scheme is two (the present insurance versus PAYD and present insurance versus PHYD), the binary logistic model is initially considered appropriate.

The fixed effects modeling approaches treat parameters as constant (fixed) across observations, meaning that the effect if any individual explanatory variable is the same for each observation or individual (19). However, to account for unobserved heterogeneity, random-parameter models are applied, assuming that the estimated parameters vary across observations. Mc Fadden and Train (7) and Train (14) consider this model as a highly flexible model that can account for the standard logit limitations and at the same time allows for random variation across observations. In these models some parameters are held fixed across observations while others are allowed to be random and follow a distribution (e.g. normal, lognormal, uniform, etc.).

Following Mc Fadden and Train (7) and Train (17), a function determining discrete outcome probabilities is considered:

$$T_{in} = \beta_i X_{in} + \varepsilon_{in} \quad (1)$$

A mixed logit model is any model whose choice probabilities can be expressed in the form:

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \quad (2)$$

where $L_{ni}(\beta)$ is the logit probability evaluated at parameters β:

$$L_{ni}(\beta) = \frac{e^{V_{ni(\beta)}}}{\sum_{j=1}^{J} e^{V_{nj(\beta)}}} \quad (3)$$

f(β) is a density function, $V_{ni}(\beta)$ is the observed portion of the utility, which depends on the parameters β. If utility is linear in β, then

$$V_{ni}(\beta) = \beta' x_{ni} \quad (4)$$

Then, the mixed logit probability takes the usual form:

$$P_{ni} = \int \left(\frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}}\right) f(\beta) d\beta \quad (5)$$

Mixed logit is a mixture of the logit function evaluated at different β's with f (β) as the mixing distribution. Estimation of the mixed logit model takes place by using simulation methods due to the difficulty in computing probabilities. More details about the mixed logit model can be found in (15). Train (17), provides a review of sampling techniques, but one of the most popular technique is considered to be the Halton draws (15), which were proposed by Halton (18).

RESULTS

In this paper two distinct mixed logit models were developed; one mixed logit model in order to investigate which factors affect the choice of present insurance policy versus PAYD and one mixed logit model for present insurance policy versus PHYD. A common issue when fitting mixed logit models is the determination of which parameters should be random and which should be fixed (19). Moore et al. (19) suggest starting with all possible independent variables and then gradually reduce them. For that reason, many different trials were conducted.

The next two subsections illustrate the proposed mixed logit models. In these models, 200 Halton draws were used. The parameters which were found to be random, were those whose standard deviations differ significantly from zero as Train (16) and Milton et al. (13) suggest. On the other hand, parameters whose standard deviations are not 95% statistically significant are considered as fixed across observations. It is noted that proposed random parameters followed the normal distribution. In order to present the performance of the model, goodness-of-fit measures such as log-likelihood and McFadden R2 are calculated.

Pay As You Drive Scheme (PAYD)

The final model for the PAYD scheme is presented on Table 3. The model shows an adequate fit in terms of likelihood ratio test (log-likelihood of empty model versus log-likelihood of the full model) as well as McFadden R^2. More specifically, the likelihood ratio test was 61.19, and the McFadden R^2 was 0.2332, indicating a reasonable fit of the model.

The variable "Km" and the variable "Cost" (which are alternative specific variables) as well as the constant term, were set to random following the normal distribution across observation.

However, only the standard deviation of the Km was found to be statistically different from zero. Therefore, the other two variables (constant term and cost) are considered fixed. The variable Km was found to have a mean value of 0.228 and a standard deviation 0.126. Therefore:

$Z = \frac{0-0.228}{0.126} = -1.809$.

According to the Z score table and the normal distribution function 3.52% of observations are lower than zero. This means that in about 96.48% of observations, Km is associated with increased likelihood of selecting PAYD while only 3.52% of observations show a negative correlation. Therefore, in the vast majority of cases, it can be concluded that as offered percentage reduction in driven mileage decreases, it is more likely that the driver chooses the PAYD policy. The cost parameters was considered as fixed, therefore, the negative sign of the beta coefficient (-0.154) denotes that as the cost reduction is lower, drivers are more likely to choose the present insurance.

The interpretation of the rest fixed parameters is more straightforward. The beta coefficient of variable EDU1 has positive sign (3.182), therefore people with primary education are more likely to choose PAYD when compared with drivers with secondary education which is the reference category for this variable. The odds ratio was calculated to be 24.104, meaning that drivers with primary education are almost 24 times more likely to choose PAYD than drivers with secondary education.

The negative value of the coefficient of USAGE_PC variable (-3.93), denotes that drivers who are more familiar with personal computer usage are more likely to choose the present insurance rather than the PAYD policy. The odds ratio was 0.02, meaning that drivers who are not familiar with personal computers are almost 50 times more likely to choose the PAYD.

On the other hand, familiarity with smartphone use is more likely to make drivers choose the PAYD policy, as the beta coefficient was found to be positive (1.138). The odds ratio is 3.122, indicating that the probability to select the PAYD scheme is 3.122 times higher for drivers who use smartphones than those who do not.

Lastly, the gender variable shows that female drivers tend to prefer the PAYD compared to males. More specifically, probability to select PAYD is almost twice higher than males.

TABLE 3 Mixed logit Model Estimates (PAYD)

Variables	Estimate	Standard error	p-value	Conclusion	Odds ratio
Random parameters (normal distribution)					
Constant term	2.104	1.780	0.237	non-significant	8.202
Standard deviation of constant term	0.939	0.602	0.119	non-significant	-
Km	0.228	0.055	0.000	95% significant	1.256
Standard deviation of Km	0.126	0.044	0.004	95% significant	-
Cost	-0.154	0.032	0.000	95% significant	0.857
Standard deviation of Cost	0.008	0.284	0.977	non-significant	-
Fixed parameters					
EDU1	3.182	1.640	0.052	90% significant	24.104
USAGE_PC	-3.930	1.766	0.026	95% significant	0.020
SMARTPHONE	1.138	0.448	0.011	95% significant	3.122
GENDER_F	0.585	0.330	0.076	90% significant	1.795
Log-likelihood of the empty model	-259.279				
Log-likelihood of the full model	-198.100				
McFadden's pseudo R^2	0.2332				

Pay As How You Drive (PHYD)

The final model for the PHYD scheme is presented on Table 4. The model shows an adequate fit in terms of likelihood ratio test (log-likelihood of empty model versus log-likelihood of the full model) and McFadden R^2.

In this model, the constant term as well as the variables “Km”, “Cost” and “Speed” were set as random variables and also normally distributed. More specifically, Km has a mean value of 0.114 and a standard deviation of 0.061, Cost has a mean of -0.179 and standard deviation 0.065, while Speed has a mean value of 0.091 and 0.077. On the other hand, the constant term was found to have a mean value of -1.789 and standard deviation 1.197.

The interpretation of the random parameters is similar to the previous model by calculating the Z-scores and use the Z-tables, since all random parameters were normally distributed. Concerning Km, the calculated Z-values indicate that 97% of observations have a positive correlation with PHYD meaning that as the percentage change in km, tends from negative to zero (reduction is lower) the probability of selection of PHYD increases. Change in speed (variable Speed) has a similar interpretation, and results indicate that about 11% of observations have a negative association with PHYD while 89% have a positive association with PHYD. The mean value of the beta coefficient was found to be 0.091. This means that as the percentage reduction in speed tends to zero, the driver is more likely to choose the PHYD policy scheme.

On the contrary, variable Cost has a negative mean value as in the previous model, indicating that the percentage reduction in cost tends to be zero, the present policy is more probable to be selected by drivers. This is also supported by the Z score which indicates that about 99.7% of observations show a negative correlation of cost and PHYD.

The interpretation of the fixed parameters in this model is straightforward as in the PAYD model. Age was found to be statistically significant for the PHYD scheme and its interpretation was expected. More specifically, the beta coefficients of AGE4 and AGE5 have negative signs, indicating that drivers 40-50 years old and older than 50 years old are more likely to prefer the present insurance policy compared with younger drivers. More specifically, young drivers are almost 2.5 times and almost 3 times more probable to choose the PHYD policy, compared to drivers 40-50 years old and older than 50 years old respectively. Familiarity with smartphone use was found to be significant and expected. Its beta coefficient was 0.627, indicating that familiarity with smartphone and applications suggests high probability for drivers choose the PHYD scheme (similarly to the PAYD) compared to the present policy. In other words, the probability of PHYD selection by users familiar with smartphone use is 1.872 times higher than those who report low familiarity. Lastly, the beta coefficient of the gender variable shows that female drivers would prefer the PHYD compared to male drivers (2.731 more likely than males).

TABLE 4 Mixed logit Model Estimates (PHYD)

Variables	Estimate	Standard error	p-value	Conclusion	Odds ratio
Random parameters (normal distribution)					
Constant term	-1.789	0.429	0.000	95% significant	0.167
Standard deviation of constant term	1.197	0.270	0.000	95% significant	-
Km	0.114	0.017	0.000	95% significant	1.121
Standard deviation of Km	0.061	0.027	0.022	95% significant	-
Cost	-0.179	0.025	0.000	95% significant	0.836
Standard deviation of Cost	0.065	0.025	0.009	95% significant	-
Speed	0.091	0.020	0.000	95% significant	1.095
Standard deviation of Speed	0.077	0.022	0.001	95% significant	-
Fixed parameters					
AGE4	-0.846	0.274	0.002	95% significant	0.429
AGE5	-1.176	0.433	0.007	95% significant	0.309
SMARTPHONE	0.627	0.309	0.042	95% significant	1.872
GENDER_F	1.005	0.244	0.000	95% significant	2.731
Log-likelihood of the empty model	513.250				
Log-likelihood of the full model	-416.500				
McFadden's pseudo R^2	0.216				

CONCLUSIONS

Within this paper, a methodological approach is proposed to identify the parameters that affect users' willingness to pay for alternative usage-based motor insurance pricing schemes such as PAYD and PHYD. A mixed logit model is developed to investigate and assist in the better understanding of the effect of driving characteristics, drivers' demographics and the price of vehicle insurance premiums on vehicle insurance choice. For that reason, a questionnaire was designed and administered to 100 participants including both revealed and stated preference questions regarding current and alternative insurance schemes.

Data from the stated preference questionnaire was analyzed using a mixed logit model (random parameter binary logistic model). Two distinct mixed logit models were developed; one mixed logit model to investigate the factors influencing the choice of present insurance policy over PAYD and one for present insurance policy over PHYD.

Results indicated both for PAYD and PHYD that women and smartphone owners are more likely to choose a new insurance scheme. Kilometers and cost reduction were also found to affect similarly the choice for both UBIs i.e. the higher the kilometers reduction the lower the probability of the UBI scheme to be chosen and the higher the cost reduction the higher the probability of the UBI scheme to be chosen by a user. Moreover, the higher the speed reduction imposed to the user the lower the probability of the UBI scheme to choose it.

It was also found that people over 40 years old are less likely to choose PHYD insurance which is supported by descriptive statistics described in Data section. Finally, people with lower education are more likely to choose PAYD insurance which is probably explained by the fact that they are generally more receptive to new technology.

Future research could carry out surveys in different countries and perhaps set up different scenarios, including more parameters. Lastly, alternative models to account for heterogeneity could be utilized, for example the latent class model.

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