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ScienceDirect

Procedia - Social and Behavioral Sciences 00 (2011) 000–000

Procedia Social and Behavioral Sciences

www.elsevier.com/locate/procedia

15th edition of the Euro Working Group on Transportation, EWGT 2012; Paris; September 2012

Comparing effects of eco-driving training and simple advices on driving behavior

Cindie Andrieu and Guillaume Saint Pierre*

IFSTTAR, IM, LIVIC, 14, route de la minière, 78000 Versailles-Satory, France
E-mail : cindie.andrieu@ifsttar.fr and guillaume.saintpierre@ifsttar.fr

Abstract

Eco-driving style is widely known to induce up to 20% fuel consumption reduction, but little is known on the effects of different learning methods. In order to evaluate the potential impacts of future ecological driving assistance system (EDAS), two kinds of experiments are analyzed in this paper: In the first one, simple advices are given to the participants, while in the second one, full courses with eco-driving experts were used. Different kind of statistical models are discussed, among which we choose to apply the ordinary logistic regression to assess the effects of each driving advice separately.

Keywords: eco-driving; logistic regression; driving behavior.

1. Introduction

Driving more efficiently is part of the solution to reduce the surface transportation greenhouse gas emissions but it is a highly complex task, comprising over hundreds of separate tasks (Walker et al., 2001). Drivers need to simultaneously control the vehicle, adjust their speed and trajectory according to driving environment, deal with hazards, and make strategic decisions such as navigation to progress toward their goal (Young et al., 2010). Since climate change and humanity responsibility has been widely accepted, many drivers have a new goal in mind: fuel efficiency. Eco-driving style is therefore often referred as smart driving because of the necessary complex trade off between the multiple goals the driver has to manage with. Studies usually simplifies the green way to drive using simple advices easily

* Corresponding author. Tel.: +33 (0) 1 40 43 29 33.

understood by drivers (CIECA, 2007), but sometimes leading to a misunderstanding of the fuel efficient driving strategy. Other studies used trial experiments before and after a training program to assess the eco-driving impact (Symmons et al., 2009). **Effects of eco-driving on fuel consumption are well described in the literature, but results are often optimistic: CO2 emissions reduction can be up to 30% according to many studies. The key question for policy makers is "how big" of an emission reduction we can get by encouraging an eco-driving style, taking into account the diversity in the way to learn eco-driving: just reading a few driving tips, taking a course with a professional, or doing practical exercises with equipped vehicles?… Moreover, there is a need to understand the best way to teach and learn eco-driving style, especially for young drivers.**

This work present the statistical analysis of two different data sets, one with subjects following simple eco-driving advices, the other with subjects driving the way they learned in a course with professional eco-drivers. For the analysis needs, eco-driving style is summarized into four different simple advices, each one of them being associated to a quantitative indicator build to reflect the associated driving behavior. Different kind of statistical models are discussed, among which we choose to apply the ordinary logistic regression to assess the effects of each driving advice separately. The significance of the differences for each indicator between normal and eco-driving trips allow us to evaluate which advice is practically used by the drivers, according to the way they learned eco-driving. The same analysis is done for each different speed limit zone to take into account the effects of the driving environment.

2. The experiments

2.1. Experiment 1: simple advices on eco-driving

The experiment goal was to clearly identify two classes of driving behavior on the same test track: "normal" and fuel efficient way to drive commonly known as "eco-driving". Twenty drivers participated in this experiment that took place in June and July 2009 in Ponchartrain (Yvelines) in France. Four of these drivers were eco-driving instructors while others were recruited among one thousand persons working in two different research institutes. In order to minimize traffic influence, the chosen route is of inter-urban type and a length of 14km. The trips were all performed under free flow conditions and with dry weather. The vehicle used was a petrol-driven Renault Clio III with manual gearshift. First of all, the journey is discovered by the subjects while seeing the experimenter driving and giving safety and direction instructions. Then, the trip was driven twice by each driver: once while driving normally, and secondly while following the "Golden Rules" of eco-driving extracted from the Ecodrive project (Ecodrive (2009)) and summarized in . These rules were given just before the ecological trip. To eliminate a learning effect of the journey, trip's order has been counter-balanced. An on-board logging device was used to monitor key driving parameters. The device is connected to the controller area network (CAN) of the vehicle, logging most of the relevant parameters related to engine state, vehicle dynamic, and driver actions on pedals. The vehicle has been also equipped with a GPS, a camera in front of the vehicle and a fuel flow meter. We used a fuel flow meter DFL1x-5bar to validate the fuel consumption logged with the CAN. Additional variables were post-processed such speed limits, gear ratio, and many indicators inspired from Ericsson (2001).

2.2. Experiment 2: eco-driving training

Nineteen drivers (who have not participated in the experiment 1) participated in this experiment that took place near Toulouse in 2004. The trials goal was to evaluate the effect of an embedded EDAS produced by the GERICO project funded by the French program of research, experimentation and innovation in land transport (Barbé et al., 2008). The original design was to compare a control group, a group applying eco-driving, and another group using the system without any advices. For the purpose of this study, only data for the eco-driving group was used. The chosen route contains various network categories (urban, rural, motorway) and has a length of 70km. The vehicle used was a Renault Megane Scenic with a four-speed sequential gearbox. The trip was driven twice by each driver: once while driving normally and secondly after an eco-driving training with professional eco-drivers. In this case, trips are not counter balanced and effects of the eco-driving teaching may be over estimated because of a learning effect.

3. Methodology

3.1. Selection of indicators associated with each of the main rules of eco-driving

Driving style to reduce fuel consumption is related to the implementation of the four main eco-driving rules set out in . Due to this link, each of these instructions was associated with an indicator. The proposed indicators are summarized in . So the first rule state to shift up early. Therefore, it is natural to associate the indicator *AvgRPMShiftUp* which is the average engine speed at the shift into a higher gear. The second rule is related both to the gear and the engine speed.

Table 1. Main rules of eco-driving and indicators associated

Instruction	Indicator	Abbreviation
1. Shift up as soon as possible: Shift up between 2.000 and 2.500 revolutions per minute.	Average engine speed at the shift into a higher gear.	Avg_RPM_Shift_Up
2. Maintain a steady speed: Use the highest gear possible and drive with low engine RPM.	Index of gear ratio distribution and engine speed associated.	Index_Gear_RPM
3. Anticipate traffic flow: Look ahead as far as possible and anticipate the surrounding traffic.	Positive Kinetic Energy.	PKE
4. Decelerate Smoothly: When you have to slow down or to stop, decelerate smoothly by releasing the accelerator in time, leaving the car in gear.	Percentage of time in engine brake.	Time_Engine_Brake

So we created an indicator, called *IndexGearRPM*, summarizing these two variables and calculated as follows:

$$IndexGearRPM = \frac{1}{3500}(TimeNeut \times AvgRPMNeut + Gear1 \times AvgRPMGear1 + \cdots + Gear5 \times AvgRPMGear5) \quad (1)$$

where *Time_Neutral* is the percentage time in neutral gear, *AvgRPMNeut* is the average engine speed in neutral gear, *Gear1* is the percentage time in gear 1 (with pressing the accelerator pedal), etc. Note that the condition of pressing the accelerator pedal ensure to ignore the time in engine brake which is associated to the fourth rule. Note also that the division by 3500 is just a normalization factor. Then the third rule related to the anticipation of traffic is associated to the parameter PKE (Positive Kinetic Energy) calculated as follows:

$$PKE = \frac{\sum (v_f^{\,2} - v_i^{\,2})}{x} \quad \text{when} \quad \frac{dv}{dt} > 0 \quad (2)$$

where v_f and v_i are respectively the final and the initial speed at each time interval for which $\frac{dv}{dt} > 0$, and

X is the total distance travelled. This indicator represents the ability to keep the vehicle's kinetic energy as low as possible. So a nervous driving will be associated with a high PKE, and conversely a smoothly driving will be associated with a PKE close to zero. Finally, the fourth rule is naturally associated with the percentage of time in engine brake characterized by the following conditions: non zero speed, no neutral, no pressure the brake pedal and the accelerator pedal.

3.2. Statistical models

The objective of this study is to compare effects of simple advices (experiment 1) and eco-driving training (experiment 2) on driving behavior. Our approach relies on developing a predictive model of economic driving behavior based on easily interpretable variables. Assuming trips are clustered according to the two driving conditions, it is worth trying a statistically based approach to predict the driving style.

3.3.

Such models are well suited in estimating the relationship between an outcome variable and a set of explanatory variables. In this paper, the outcome variable is from a binary distribution with two possible values:

$$Y_{ij} = \begin{cases} 1 \; if \; ecodriving \\ 0 \; if \; not \end{cases} \quad i = 1, \dots, I \; ; \;\; j = 1, \dots, T_i \tag{3}$$

where I is the number of drivers and T_i is the number of observations for the driver i. Logistic regression is a form of statistical modeling that is often appropriate for binary outcome variables. Assume Y_{ij} follows a Bernoulli distribution with parameter $p_{ij} = P(Y_{ij} = 1)$ where p_{ij} represent the probability that the event occurred for the observation Y_{ij}. The relationship between the event probability p_{ij} and the set of factors is modeled through a logit link function with the following form:

$$logit(p_{ij}) = \log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = X'_{ij}\beta \tag{4}$$

where X_{ij} is the vector of explanatory variables and β is the vector of regression parameters (Agresti, 2002). The ordinary logistic regression assumes independent observation and the vector β is estimated by the method of maximum likelihood. However, the assumption of data independence does not suit our data very well, as it will contain unavoidable driver-specific correlations (i.e. observations from the same driver are assumed to be correlated) that should be treated as random effects. The standard errors from the

ordinary logistic regression are then biased because the independence assumption is violated.
To account for these driver specific correlations as random effects, more sophisticated statistical models need to be applied. These models are particularly useful for naturalistic driving study (Guo and Hankey, 2010; Benminoun et al., 2011) and specially event based approach (EBA) which basic principle is to identify time segments that can be predictive of an event (e.g. crash, near-crash, …). Indeed, these models include additional parameters to deal with correlations, and confounding factors are viewed as explicative variables that can be used to predict event probability. One such model is the "Generalized Estimated Equations" (GEE) model or marginal models, originally developed to model longitudinal data by Liang and Zeger (1986), which assumes that observations are marginally correlated. Another approach for modeling correlated data is "Generalized Linear Mixed Models" (GLMM). The GLMM model introduces a random effect specific to each subject whereas the GEE approach models the marginal distributions by treating correlation as a nuisance parameter. Therefore the inference is individual (subject-specific approach) in contrast to marginal models that model the average population (population-averaged approach). However, in our study, we didn't use these two sophisticated statistical models because of the small sample size (see Section 4.2 for more details). So we used only ordinary logistic regression models.

4. Results

4.1. Overall effects of eco-driving rules and eco-driving training

Numeric results are summarized in . A paired *t*-test was performed to assess whether the mean of each parameter differ significantly according to the driving style. indicates the p-values of these tests. Among the most interesting ones, the average fuel consumption across drivers decreased by 12.5% between normal driving and eco-driving for the experiment 1 and decreased by 11.3% for the experiment 2. These similar results between the two experiment show that it seems quite simple to reduce fuel consumption by applying some basic rules of eco-driving. The average speed decreased by 5.8% for the experiment 1 and 10.1% for the experiment 2, and the percentage of time beyond the legal speed limit decreased by 30.1% for the experiment 1 and 36.1% for the experiment 2.

Table 2. Effects of eco-driving rules on different parameters

Parameter	Description	Experiment 1			Experiment 2		
		Mean "Normal"	Mean "Eco"	Variation (%)	Mean "Normal"	Mean "Eco"	Variation (%)
AvgFuelConsum	Average fuel consumption (l/100km).	6.86	6.00	−12.5***	9.01	7.99	−11.3***
AvgRPMShiftUp	Average engine speed at the shift into a higher gear (associated with rule 1).	2737.5	2232.8	−18.4***	3177.3	2465.6	−22.4***
IndexGearRPM	Index of gear ratio distribution and engine speed associated (associated with rule 2).	61.0	52.9	−13.3***	70.8	60	−15.3***
PKE	Positive Kinetic Energy (associated with rule 3).	0.343	0.243	−29.2***	0.293	0.197	−32.8***
TimeEngineBrake	Percentage of time in engine brake (associated with rule 4).	20.3	26.3	+29.6**	16.2	16.8	+ 0.04
AvgSpeed	Average speed (km/h)	50.85	47.89	−5.8**	61.45	55.22	−10.1***
AvgAccel	Average acceleration (ms^{-2})	0.498	0.387	−22.3***	0.596	0.473	−20.6***

AvgDecel	Average deceleration (ms^{-2})	-0.619	-0.523	-15.5^{***}	-0.672	-0.599	-10.9^{***}
AvgRPM	Average engine speed (rpm)	2097.4	1835.5	-12.5^{***}	2379.6	2009.6	-15.5^{***}
TimeNonLegalSpeed	Percentage of time beyond the legal speed limit	37.9	26.5	-30.1^{***}	28.5	18.2	-36.1^{***}

$^{*}\ p < 0.05$; $^{**}\ p < 0.01$; $^{***}\ p < 0.001$.

These reductions reflect a better compliance with speed limits with economical driving regardless of the learning mode. As regards the application of eco-driving rules, the four associated indicators are significantly different among the two driving conditions, indicating that the instructions were applied with the two learning mode. However, in the experiment 2, the engine brake (associated with the fourth rule of eco-driving) does not seem to have been used correctly. Furthermore, the average acceleration and deceleration both decrease significantly in the two experiments which is in agreement with the second and the third rules of eco-driving.

4.2. Separated effects of the main eco-driving rules

The aim of this study is to assess the effects of each driving advice after two learning mode: one with subjects following simple eco-driving advices (experiment 1), and the other with eco-driving training (experiment 2). Our approach is to construct, for each experiment, a predictive model of the probability of being in an eco-driving situation using a binomial logistic regression model with the four indicators in as explanatory variables. According to our experiment, we predict the binary variable named ”Trip” which takes the value 0 in normal driving (noted ”normal”) and 1 in eco-driving (noted ”eco”). Thus, the significance of the differences of each indicator between normal and eco-driving trips allow us to evaluate which advice is practically used by the drivers, according to the way they learned eco-driving.

However, in our two experiments, both the number of clusters (20 in the experiment 1 and 19 in the experiment 2) and the cluster size (2 in the two experiments) are small, which implies various constraints. In a first part, the smallness of our sample size limits the number of predictors for which effects can be estimated precisely. Peduzzi et al. (1996) suggests there should ideally be at least ten outcomes of each type for every predictor. This result constrains us to assess the effects of each driving advice separately and consequently to construct one logistic regression model with each of the four indicators as predictor. In a second part, the smallness of our sample size does not allow us to use the appropriate statistical models taking into account driver specific correlations. Indeed, we tested the GEE method using the PROC GENMOD of the SAS software, but the parameters estimates were closed to zero. Ziegler et al. (1998) recommend an application of the GEE only, if the number of clusters is at least 30 for a cluster size of about 4 for a low to moderate correlation. We also tested the generalized linear mixed models using the PROC GLIMMIX of SAS but a statement indicates that one of the estimated variance parameters was negative. This result is an underestimate of the true variance component that occurs when the number of observations per random effect category is small or when the ratio of the true variance component to the residual is small. Moreover, several studies (Moineddin (2007), Theall (2011)) have shown that parameters estimates are unbiased with either fixed or random effects logistic models when the number of clusters and the cluster size are small. However these studies show that the estimates of the random intercept and random slope have larger biases compared to the fixed effect parameters. Thus, later in this paper, we use an ordinary logistic regression.

The logistic model can be written as:

$$Logit[P(Trip = Eco)] = \alpha + \beta X \quad (5)$$

where α is the intercept, X is one of the four indicators associated with the main rules of eco-driving () and β is the parameter estimate of the predictor X. The results from each logistic model are listed in Table 3 for the experiment 1 and Table 4 for the experiment 2. For each logistic model, we indicate the explanatory variable X, the estimated parameter β, its standard error SE and the p-value of the Wald test. We also indicate the odds ratios (OR) and their 95% Wald confidence limits. The usefulness of each model is measure by the Nagelkerke R^2, denoted R_N^2, which is an adjusted version of the Cox & Snell R^2 and which is similar to the coefficient of determination R^2 in linear regression. This parameter does not measure the goodness of fit of the model but indicate how useful the explanatory variable is in predicting the response variable. Finally, the predictive power of each model is measure by the area under the ROC curve (AUC). This parameter, ranges from zero to one and identical to the concordance index, assess the discrimination power of the model. In our study, it measures the model's ability to discriminate between eco-driving trips versus normal trips. More details on these various parameters are given in Agresti (2002) or Hosmer and Lemeshow (2000).

In Table 3 and Table 4, the four logistic models, assessing the implementation of each rules of eco-driving, are ranked in descending order of both parameters R_N^2 and AUC and thus represents the order of implementation of each driving advice. Table 3 shows that all the indicators are significant (p-value lower than 0.01 and 95% confidence interval including one) in the experiment 1 but the indicators associated with the first three rules are most significant: relatively high R_N^2 reflecting that the three indicators *AvgRPMShiftUp*, *IndexGearRPM* and *PKE* are useful in predicting eco-driving trip, and AUC greater than 0.8 reflecting a high discriminatory power of this three models. On the contrary, the indicator *TimeEngineBrake* is not very useful in predicting eco-driving trip (R_N^2=0.289) even if the discriminatory power of this model is acceptable (0.7 ≤ AUC ≤ 0.8). Table 4 shows the results obtained in the experiment 2. The results are globally similar to those obtained in the experiment 1 except that the indicator *TimeEngineBrake* is no longer significant (one is excluded of the 95% confidence interval) and the model associated is not very useful in predicting eco-driving behavior (R_N^2 close to zero and AUC close to 0.5 indicating poor discrimination of the model).

Table 3. Experiment 1: logistic regression models with each of the four indicators associated with the main rules of eco-driving and ranked in descending order of implementation of each driving advice.

Models	β	SE	OR	95% CI	R_N^2	AUC
X= AvgRPMShiftUp (Rule 1)	-0.0068^{**}	0.002	0.993	0.989 - 0.997	0.608	0.908
X=PKE (Rule 3)	-34.0893^{**}	10.622	< 0.001	< 0.001 - < 0.001	0.594	0.898
X= IndexGearRPM (Rule 2)	-0.3068^{**}	0.103	0.736	0.601 - 0.901	0.491	0.866
X= TimeEngineBrake (Rule 4)	0.1849^{**}	0.071	1.203	1.047 - 1.383	0.289	0.780

$^{*}\ p < 0.05;\ ^{**}\ p < 0.01;\ ^{***}\ p < 0.001.$

SE: standard error; OR: odds ratio; CI: confidence interval; R_N^2: Nagelkerke R^2; AUC: area under the ROC curve.

Table 4. Experiment 2: logistic regression models with each of the four indicators associated with the main rules of eco-driving and ranked in descending order of implementation of each driving advice.

Models	β	SE	OR	95% CI	R_N^2	AUC
X= IndexGearRPM (Rule 2)	-1.4262^{*}	0.677	0.240	0.064 - 0.906	0.922	0.989
X= AvgRPMShiftUp (Rule 1)	-0.0126^{**}	0.004	0.987	0.979 - 0.996	0.878	0.976
X=PKE (Rule 3)	-63.7126^{**}	21.715	< 0.001	< 0.001 - < 0.001	0.744	0.952
X= TimeEngineBrake (Rule 4)	0.0254	0.065	1.026	0.902 - 1.166	0.005	0.568

$^{*}\ p < 0.05;\ ^{**}\ p < 0.01;\ ^{***}\ p < 0.001.$

SE: standard error; OR: odds ratio; CI: confidence interval; R_N^2: Nagelkerke R^2; AUC: area under the ROC curve.

4.3. Eco-driving effects for different speed limits

Assuming that eco-driving behavior depends on the road conditions, previous logistic models were extended to more complex models taking into account the speed limits. The variable "Speed limit" is used as a stratification variable in order to derive specific models. Thus, for each trip of the two experiments, sections corresponding to a specific speed limit were merged for analysis. The calculation of the four indicators defined in was then adapted on these new trip to take into account the grouping of sections not necessarily continuous. Table 5, Table 6 and Table 7 contain the estimated parameter, its standard error, the Nagelkerke R^2 and the AUC for the three main speed limits: 50km/h, 70km/h and 90km/h. Table 5 shows similar results for the two experiments when the speed limit is 50km/h: the three indicators *AvgRPMShiftUp*, *IndexGearRPM* and *PKE* are most significant while the indicator *TimeEngineBrake* is not very useful in predicting eco-driving behavior. Table 6, corresponding to the speed limit 70km/h, shows that in the experiment 1, the four driving advices have been applied while in the experiment 2, only the first three advices have been applied. Finally, Table 7 shows that when the speed limit is 90km/h, the indicators *AvgRPMShiftUp* and *IndexGearRPM* are most significant in the two experiments whereas the indicator PKE is less significant than with the previous speed limitations. As for areas limited to 50km/h, the indicator *TimeEngineBrake* is not useful in predicting eco-driving behavior and in the experiment 1, the estimated parameter is negative (but no significant) which means that engine brake seems to have been less used during eco-driving trips than during normal trips.

Table 5. Logistic regression models for 50km/h speed limit.

Models	Experiment 1				Experiment 2			
	β	SE	R_N^2	AUC	β	SE	R_N^2	AUC
X= AvgRPMShiftUp (Rule 1)	-0.007^{***}	0.002	0.62	0.909	-0.012^{**}	0.004	0.83	0.964
X= IndexGearRPM (Rule 2)	-0.371^{**}	0.124	0.56	0.903	-0.908^{*}	0.362	0.85	0.978
X=PKE (Rule 3)	-36.022^{**}	11.969	0.59	0.896	-34.859^{**}	11.301	0.64	0.922
X= TimeEngineBrake (Rule 4)	0.108^{*}	0.045	0.24	0.745	0.074	0.074	0.07	0.676

$^{*}\ p < 0.05$; $^{**}\ p < 0.01$; $^{***}\ p < 0.001$.

SE: standard error; R_N^2: Nagelkerke R^2; AUC: area under the ROC curve.

Table 6. Logistic regression models for 70km/h speed limit.

Models	Experiment 1				Experiment 2			
	β	SE	R_N^2	AUC	β	SE	R_N^2	AUC
X= AvgRPMShiftUp (Rule 1)	-0.005^{**}	0.002	0.48	0.871	-0.013^{**}	0.005	0.88	0.986
X= IndexGearRPM (Rule 2)	-0.293^{**}	0.105	0.43	0.851	-0.459^{***}	0.139	0.76	0.938
X=PKE (Rule 3)	-25.350^{***}	7.705	0.46	0.863	-31.830^{**}	10.967	0.61	0.922
X= TimeEngineBrake (Rule 4)	0.178^{**}	0.063	0.35	0.795	0.034	0.050	0.02	0.562

$^{*}\ p < 0.05$; $^{**}\ p < 0.01$; $^{***}\ p < 0.001$.

SE: standard error; R_N^2: Nagelkerke R^2; AUC: area under the ROC curve.

Table 7. Logistic regression models for 90km/h speed limit.

Models	Experiment 1				Experiment 2			
	β	SE	R_N^2	AUC	β	SE	R_N^2	AUC
X= AvgRPMShiftUp (Rule 1)	-0.005^{**}	0.002	0.47	0.868	-0.019^{*}	0.009	0.90	0.989
X= IndexGearRPM (Rule 2)	-0.225^{**}	0.077	0.43	0.850	-0.494^{**}	0.159	0.78	0.956
X=PKE (Rule 3)	-14.054^{*}	5.463	0.27	0.745	-21.121^{*}	8.280	0.33	0.758
X= TimeEngineBrake (Rule 4)	-0.015	0.080	0.001	0.521	0.038	0.051	0.02	0.651

$^{*}\ p < 0.05$; $^{**}\ p < 0.01$; $^{***}\ p < 0.001$.

SE: standard error; R_N^2: Nagelkerke R^2; AUC: area under the ROC curve.

5. Conclusion

This study provides the statistical analyses of two learning mode of eco-driving: one with simple eco-driving advices and the other with eco-driving training. The study of different parameters like average fuel consumption, average speed, or average acceleration shows a real positive impact of eco-driving style regardless of the learning mode.

The association of each of the main eco-driving rules with a quantitative indicator allows us to assess the effect of each driving advice separately using logistic regression models. It is shown that drivers succeed efficiently in applying advices related to constant speed or gearshift strategy regardless of the learning mode of eco-driving, while they are less efficient in using engine brake (small parameter influence for experiment 1 and insignificant for experiment 2). The same analysis is done for each different speed limit zone in order to take into account the effects of the driving environment. Results are all together in line although significant differences are found for the engine brake related rule. On 70km/h limited areas the engine brake was not correctly used in experiment 2 (with eco-driving training) while all the four driving advices were correctly implemented in experiment 1 (with simple advices). On the contrary, on 90km/h limited areas, the 4th rule effect is insignificant for both experiments although the engine brake seems to have been less used during eco-driving trips than during normal trips.

Golden rules indicators show that fuel efficient driving is better implemented after a course than just applying eco-driving tips (greater R_N^2 and AUC). Differences are small due to the bias introduced by the presence of an experimenter in the car in both experiment. Suitable experimental designs and specific studies are needed to quantify precisely the size of the differences between the two leaning modes.

Data sets used in this paper are small and lack of consistency between controlled factors for each experiment (different drivers, cars, driving conditions, etc.) but it is worth trying a meta-analysis to improve veracity of the results. Effects sizes are in line all together showing the ability of our indicators to represent eco-driving capacities. Our work show that just reading simple eco-driving advices allows drivers to reduce significantly their fuel consumption and to adopt an eco-driving behavior although performances are better after a course. The important question now is to find how long a fuel efficient driving behavior last depending on the way drivers learned it. This issue will be the scope of our future research.

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