Naturalistic Driving Study for Older Drivers based on the DriveSafe App

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Abstract— **Elderly population is increasing year after year in the developed countries. However, the knowledge of actual mobility needs of senior drivers is scarce. In this paper, we present a naturalistic driving study (NDS) focused on older drivers through smartphone technology and using our DriveSafe app. Our system automatically generates a driving analysis report based on objective indicators. The proposal supposes an improvement over the traditional surveys and observers, and represents an advance over the current NDSs by using smartphones instead of complex instrumented vehicles. Our method avoids the problems of manual annotation by using an automatic method for data reduction information. Furthermore, a comparison between traditional questionnaires and information provided by our system is carried out and conclusions are presented.**

I. INTRODUCTION

Elderly population is increasing year after year in the developed countries. The 25% of the population in the OECD (Organization for Economic Co-operation and Development) countries will surpass 65 years by 2050 [1]. In the next 20 years, the number of elderly drivers is predicted to triple in the United States [2]. In Spain, they currently represent 18.8% of the population and 14% of the drivers with license. In 2030, one out of every three Spanish drivers will be over 65 years old [3]. Driving is a source of independence and freedom for seniors but there is some concern about the skills deterioration and losing the ability to safely operate a vehicle of this group of drivers as they get older. Elderly drivers are frequently implicated in collisions at junctions, because of misjudging the distance/speed of the other users or failing to predict a risk. Their lethality rate in traffic accident is 3.3 times higher than the rest of the population [4].

A number of previous medical studies on the elderly drivers have demonstrated the effect of physical abilities on driving safety in a theoretical way, but they have not been validated in real driving conditions [2]. The knowledge of real mobility needs of the elderly is scarce, but characterizing their individual driving behavior is key for road safety. So far, a considerable effort has been made in the development of questionnaires that report driving habits. However, these studies are limited, they are based on self-reports and their validity have not been proven [5].

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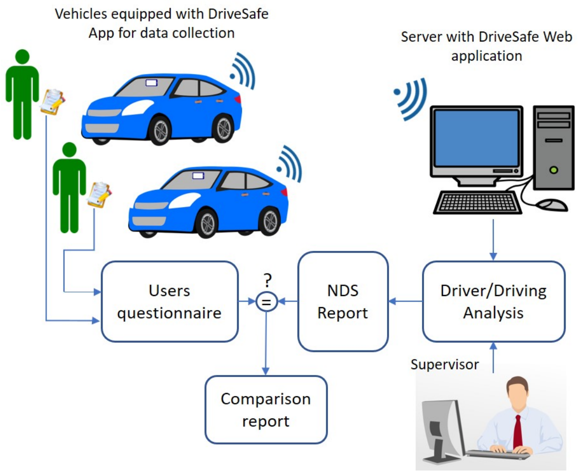

Fig. 1. Data collection and processing framework.

In recent literature, the concept of Naturalistic Driving Study (NDS) has appeared with the idea of analyzing the behavior of drivers in real environments of their daily lives and for long time periods. These studies are broken down into 4 groups: those that perform a self-assessment on the vehicle, those that make an assessment through experts, those that use an instrumented vehicle, and those based on smartphones [6].

The former suffers from the problem of self-evaluation, which, as demonstrated in [7], is not reliable when compared with objective data. Within the second group we find works like those of [8], [9], focused on older drivers. The presence of observers in the vehicle will affect the behavior of the users, causing a more careful driving. To avoid deviations due to observers, recent studies have implemented multisensorial systems for the collection of objective data in a less intrusive way in NDSs. Most use instrumented cars and are divided among those that analyze driver behavior in general, such as the SHRP2 (Strategic Highway Research Program) [10], the LISA-Q2 project [6] or the recent Advanced Vehicle Technology (AVT) Consortium of the MIT AgeLab [11]; or those focused on the junior and senior drivers analysis, such as [12] or [8]. These approaches have the problems that instrumented vehicles are expensive and difficult to replicate. Besides, they collect huge among of raw data difficult to manage. Currently, smartphones offer a cheap alternative able to be installed in the own users' vehicles. There are some applications that analyze partial indicators, such as iOnRoad App [13], or that implements limited NDSs [14], but so far they are not a reliable alternative.

Data management is one of the key issues in the current NDSs due to the huge amount of data collected by the different sensors using hundreds of instrumented vehicles driving during long periods of time. These studies are usually organized in three hierarchical levels to reduce their amount of data in order to get more easily understandable information [6]. The first level is the raw sensor data. The second is the data processed from the raw sensor data with the goal of driver analysis, including semantic information about the lane and vehicle position, lane changing events, velocity analysis, etc. The third level comprises higher level inferences such as the behavior of the drivers, aggressive analysis, driving scores, etc. Most NDSs carry out the process of data reduction in a manual way through trained supervisors who review the video segments and record a taxonomy of variables that provide information regarding user behavior. Because of the amount of the data collected in such studies, this reduction way can consume a considerable amount of time, and it is also under the interpretation of the administrator performing the task. Some recent NDSs, such as [15] and [16], suggest software tools to reduce data, resulting in a better performance and accuracy of the NDSs. However, only partial results have been presented so far.

With this background, a naturalistic driving study (NDS) through smartphone technology tested with older drivers is proposed in this paper, following the framework depicted in Fig.1. The proposed technique automatically collects driving information of each user thought a smartphone installed in his/her vehicle with the DriveSafe app running. When a WiFi connection is available, all data corresponding to each trip is sent to a remote server, loaded in a database and processed with a DriveSafe Web application in order to automatically generate a driving analysis report, based on objective indicators, which will allow the assessment of senior driver behaviors. To improve performance, a supervisor validates the results obtained by our tool. The proposal is disruptive since it supposes an improvement over the traditional surveys and observers, it represents an advance over the current NDSs by using smartphones instead of complex instrumented vehicles, and it solves the problems of manual annotation proposing an automatic method for data information reduction. Besides, a comparison between traditional questionnaires and information provided by our system is carried out.

II. DRIVING ANALYSIS USING DRIVESAFE APP

DriveSafe [17], [18] is a driver safety app for iPhones, developed by the authors, that infers driving behaviours in real-time, giving corresponding feedback to drivers and scoring their driving. In this paper, we only take advantage of the scoring capabilities of our generic app to analyze older drivers. Some modifications were carried out with this objective in mind. The main one was the inclusion of driver analysis, collecting in-cabin videos (driver position) synchronized with the ahead road video. To save memory, road and in-cabin videos were only recorded just before and after some event is launched and not in a continuous way. Different strategies were studied to perform the real-time simultaneous activation of the two iPhone cameras, but due to the privacy policies of Apple this proved to be impossible. Finally, we chose a simple but effective solution consisting in the placement of a convex mirror on the windshield, looking at the driver, and whose projection is captured in the field of view of the ahead camera, in charge of the driving analysis.

Fig. 2. DriveSafe installation for our NDS.

Fig.2 depicts DriveSafe installation process. The iPhone must be placed on a holder coupled to the windshield, just below the rear-view mirror and aligned with the relevant axes of the vehicle. Just behind must be placed the convex mirror so that its image is in the upper left corner of the rear iPhone camera. In this way, driver and driving images are synchronized and don't interfere between them. Only a slight calibration is needed just before using the app. To avoid the battery draining, we recommend plugging the iPhone to the car cigarette lighter charger. Due to length restrictions, in this paper we will only focus in the driving analysis.

DriveSafe uses the iPhone onboard sensors to provide NDSs applying computer vision and pattern recognition techniques on the phone to reduce data, following a hierarchical reduction strategy as in [6] and that we show in Fig.3. The first level is the raw sensor data collected from the iPhone sensors in the vehicle. The second level is the processed data from the first level and supposes a reduction of information and a higher abstraction level. This includes some basic information about each trip (km, hour, duration, speed, etc.), the seven events provided by DriveSafe (acceleration, braking, steering, weaving, drifting, overspeeding and car following), and some driver clues (seatbelt wearing, hands on the wheels, smoking, objects manipulation, distractions, etc). The third level of our data hierarchy comprises the higher abstraction level with the inference of driver behaviours, among three different classes (calm, drowsy and aggressive), and the inference of a global score for each trip. A deep explanation of all these indicators is out of the scope of this paper, we refer the readers to [19] for more information. Hereafter, we will proceed with a brief explanation for each of them.

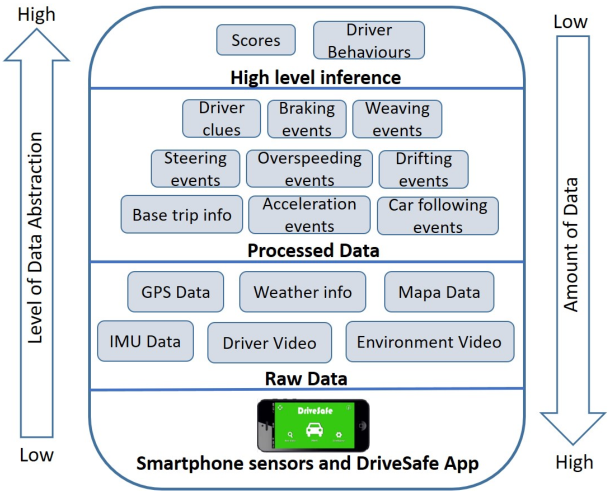

Fig. 3. Data hierarchy in our NDS.

A. Processed Data Level

Fig.4 shows a concept scheme about each of the events generated by DriveSave in the mid-level processing and that are the base to the higher inference level indicators.

Hard Acceleration. After calibration, the iPhone accelerometer z-axis is tangential to the vehicle trajectory. Then, aggressive forward acceleration events, corresponding with the hard throttle use of the driver, are detected for those values higher than a certain threshold. In practice, three different levels are applied: high, medium and low.

Hard Braking. Sudden deceleration is an indicative of harsh braking and is detected when forward acceleration is lower than a negative threshold. In practice, three different levels are applied as well.

Aggressive Steering (Turns). Taking into account that the iPhone accelerometer y-axis is perpendicular to the vehicle trajectory, high lateral acceleration corresponds to aggressive steering (right and left) and is detected in practice by imposing three different thresholds for high, medium and low level.

Weaving (Lane changes). It evaluates lane changes (left and right) performed by the driver along time. A lane change is detected using the ahead image provided by the iPhone and using image processing to calculate when the ego-vehicle position crosses one of the lane edges. Changes are classified as regular and irregular depending on the time it takes to make the change. To do that, first ten changes are used to build a normal model. After that, changes to fast or too slow regarding the normal model are assumed to be irregulars.

Drifting (High Lanex). It is based on the Lanex (fraction of Lane exits) indicator, which measures the drivers tendency to exit the lane [17]. It is defined as the fraction of a given time interval spent outside a virtual driving lane around the center of 1.2 m width. It is calculated using the road images and applying windowing techniques over the position of the vehicle in the lane during 60 s. A drifting event is detected when Lanex is over a certain threshold.

Over-Speeding. DriveSafe obtains and processes data collected from OpenStreetMap (OSM) API, which provides detailed road information through a web service. The maximum allowed speed of the current lane is taken around each second, depending of the server response, and it is compared with the current vehicle speed obtained by the GPS. If the vehicle speed is higher the allowed one during more than a second, an over-speeding event is generated. Windowing filtering is applied to avoid multiple detection corresponding to a single event.

Short car following. DriveSafe carries out a vision-based vehicle detection and tracking pipeline on the scene in real time, which was described in [18]. A multi-scale proposal and simple geometry consideration of the lane model, based on the vanishing point, are combined to overcome computational constraints. Using ego-vehicle position and the lane model the distance with the ahead vehicle is calculated. Considering the speed of our vehicle and the estimation of the ahead vehicle done by the tracking, Time-Head-Way (THW) parameter is calculated as well. If THW is lower than 0.3 s an event is generated.

B. Higher Inference Level

Two high level indicators are inferred from the events obtained in the processed data mid-level.

Driver Scoring During each trip, the processing data level detects the different events of different intensities (low, medium, high). Any single trip is scored with a value between 0 and 10, being 10 the best possible score. At the beginning of each trip the driver gets 10 points. The driver loses points depending on the number of the the different events (low (Eve_{il}), medium (Eve_{im}) and high (Eve_{ih})) per km and their intensities according to the following formula:

$$S_{trip} = 10 - \frac{1}{M}\sum_{i=1}^{M}\left(k_{il}\frac{Eve_{il}}{km} + k_{im}\frac{Eve_{im}}{km} + k_{ih}\frac{Eve_{ih}}{km}\right)$$

Being M the number of events types (M=7 in our case). The penalty constants (k_{il}, k_{im}, k_{ih}) were experimentally calculated and each event contributes to the final score with a penalty value obtained for the different intensities and scored in a different way depending of them. The higher the intensity is the greater the penalization will be. The final driver score is obtained averaging the scores for the different trips.

Driver Behaviours Classification A Gaussian model based on the penalties obtained for the seven events defined in the mid-level hierarchy was built for the calm, aggressive and drowsy behaviors in a previous setup. To do that, some drivers, different to those who perform the tests, repeated predefined routes by simulating the three behaviours according to their criteria. Data collected in these trips was used to generate the models. After each trip, events values are inputted to the Gaussian models obtaining as output the probability to belong to each of them. The trip is classified as belonging to the behavior model that gets the highest probability. We are conscious there is not an universal definition for those behaviours and they are quite subjective. However, an average model was obtained for each of them,

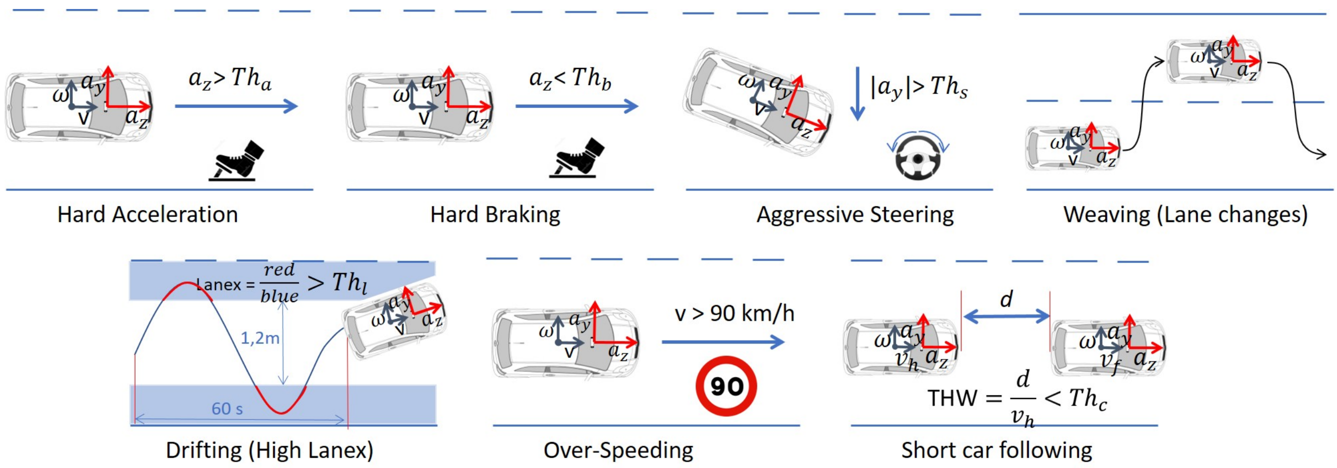

Fig. 4. Events generated in the processed data.

showing a good generalization capability in our previous work [19]. A deep study of this modelling strategy is out of the scope of this paper but will be published in the near future.

III. EXPERIMENTAL RESULTS

A. Test-bed

The recruitment process was leaded by the Spanish Research Institute in Human Factors ESM [20]. They contacted 50 drivers with the following prerequisites: over 65 years old, with driving experience (more than 20 years of driving license), with current active driver's license, and drive more than one trip a week. It is remarkable that 50% of participants use SUVs and only 12% use a small car in their trips. The search was focused on three representative cities of Spain of different sizes: Madrid (big), Seville (medium) and Oviedo (small). Finally, 23 of them agreed to participate in the project anonymously and valid data was obtained for 20 drivers (16 males and 4 females).

After signing a consent contract to participate in this study, each driver completed a questionnaire divided into 3 blocks: demographic data, data about his driving and driver behavior. Afterwards, the installation of the iPhone and the DriveSafe (DS) app was carried out in the user's vehicle. Its operation was explained and an initial demo was carried out with an ESM technician as copilot. A contact telephone number was also provided to solve doubts. After this initial test, the system was ready to collect data. The user was required to drive as he usually does (naturalist driving) with the only exception of launching the application (by clicking on the mobile screen) at the beginnig of each trip. It was recommended that, for safety, at the end of each day, the iPhone was removed from the holder, taken to user home and connected to a WiFi network so that the day's data could be sent to the server.

Each participant had the system installed between 1 and 2 weeks and the tests were conducted between October and December 2018 using 4 devices simultaneously provided by the researchers (1 iPhone 8, 1 iPhone 7 and 2 iPhone 6). At the end of the test, an ESM technician met with each user to uninstall the equipment and pass a final questionnaire about the usability of the application and improvement suggestions.

B. Accuracy of detectors

To evaluate the impact of detectors accuracy on the analysis of the NDS data reduction, table I shows F1-score classification metric for each of the events, published by the authors in previous works. For the car following analysis, detection is considered until 40 m. In the case of over-speeding, detection is 100% accurate always a 3G/4G connection with the remote OSM server is available. The impact due to this error uncertainty can be considered minor in this study because the events penalty score, which is the base for the global score and behaviour classification calculation, is based on the whole events detected for each trip. In this way, scores follow the events majority trend, despite detection uncertainty.

TABLE I

ACCURACY OF EVENTS DETECTORS

Accuracy	Events						
	Acc	Bra	Turn	Weav	Drift	Carfol	Oversp
F1-score	81%	84%	84%	95%	95%	87%	100%
Reference	[17]	[17]	[17]	[17]	[17]	[18]	[19]

C. DriveSafe Analysis Results

Table II shows the results obtained by DS for the NDS during a week. For the 20 users, 3,300 km driven during 77 h on 197 trips were analyzed. The weekly usability analysis of the vehicle is diverse. There are users who use their cars a couple of days (e.g., D14) and some others who use them almost every day doing numerous trips (D1, D20). Most of the trips are short and in urban or mixed routes (urban and interurban). The app scores the driving of the participants with an average score of 7.65 points, which is somewhat higher than the average obtained with non-senior users in some other tests performed by DS [19]. 78% of trips are classified as calm, 16.5% as aggressive and the remaining 5.5% as drowsy. These numbers show that most drivers conducted quiet rides with some drifts to drowsy behavior.

TABLE II
DRIVESAFE ANALYSIS RESULTS

Driver	Usability			Speed (Km/h)		Processed data - Events (Penalty)							Global	Behaviour		
	Time	Km	Trips	Avg	Max	Acc	Bra	Turn	Weav	Drift	Over	Carfol	Score	Cal	Agg	Drow
D1	561	435	20	47	147	**4.14**	5.82	3.91	1.23	0.90	-	**2.67**	7.34	90%	10%	0%
D2	393	244	16	37	145	1.31	4.98	5.92	1.13	1.47	-	0.52	7.81	100%	0%	0%
D3	76	36	6	28	87	0.37	2.68	0.88	3.03	2.89	-	0.00	8.6	**100%**	0%	0%
D4	14	8	2	34	128	1.69	2.06	**7.99**	2.15	2.67	-	0.00	7.65	100%	0%	0%
D5	107	71	11	40	128	**4.26**	5.50	5.48	2.06	**4.30**	-	0.25	**6.88**	82%	0%	**18%**
D6	213	149	12	42	127	1.04	1.63	5.23	**3.18**	2.55	**4.36**	0.05	7.42	50%	**36%**	14%
D7	306	199	17	39	115	0.27	2.48	6.65	0.88	0.57	-	1.84	8.19	76%	12%	12%
D8	379	278	24	44	127	0.50	1.89	1.16	1.52	**3.72**	-	0.02	8.74	92%	0%	8%
D9	198	173	16	52	138	0.27	2.95	4.55	0.27	0.64	3.03	0.03	8.32	75%	25%	0%
D10	217	125	10	35	128	0.89	3.48	6.46	0.29	0.55	0.99	0.37	8.14	100%	0%	0%
D11	22	4	3	11	49	0.00	0.00	0.00	0.63	3.52	0.00	0.00	**9.4**	**100%**	0%	0%
D12	171	37	8	13	64	0.03	1.17	0.36	1.72	**4.41**	0.70	0.00	**8.8**	88%	0%	12%
D13	136	104	11	46	121	0.03	**6.23**	7.45	0.66	1.85	**4.39**	0.26	6.96	55%	**45%**	0%
D14	10	2	2	12	43	0.00	0.00	0.00	0.00	0.00	1.00	0.00	**9.85**	**100%**	0%	0%
D15	56	25	3	27	105	1.79	**7.83**	**10.00**	3.40	1.99	-	**2.58**	**6.06**	67%	33%	0%
D16	155	95	11	37	110	0.00	0.31	0.80	**4.84**	3.39	2.63	0.01	8.29	37%	18%	**45%**
D17	261	263	5	60	172	0.11	0.83	1.94	2.82	2.39	1.23	1.19	8.5	80%	20%	0%
D18	17	18	2	64	129	1.62	3.24	6.69	0.00	0.31	1.15	0.05	8.14	100%	0%	0%
D19	275	186	8	41	135	0.32	3.42	3.54	1.13	0.92	3.43	0.17	8.15	70%	30%	0%
D20	1050	850	10	49	141	**10.00**	**10.00**	**10.00**	**6.60**	3.40	**6.36**	**3.84**	**2.84**	30%	**70%**	0%

If we analyze some representative calm drivers behaviours (D3, D11, D14), it is observed that they generate few events and that the biggest penalties come from the events related to accelerations and the position within the lane (Drifting), indicating inability of the driver to stay in the center of the lane, and his/her tendency to use the accelerator (Acc), the brake (Bra) and the steering wheel abruptly (Turn). This relaxed driving behavior leads some users to drowsy behavior, such as for D16 that presents a maximum penalty due to slow lane changes, or for D5 that gets great penalties in the drifting and acceleration events.

It should also be noted that there is a small group of drivers that performs aggressive behavior (D6, D13, D20), which correspond to lower global scores and ranging from cases like the D20, with large penalties in all events. This behavior is compatible with a stressful driving possibly due to work activities, to others like the D13 with aggressive behavior caused by over speeding.

Regarding the gender analysis, it is worth noting that the average score of the women drivers is 8.38 points, being 0.73 points higher than the average for all the drivers. In addition, 91.5% of their trips were classified as calm, being 13.5% higher than the average. These data, with the reserve due to the low number of participants, show that women drive more calmly than men.

D. Comparison between Questionnaires and DS Results

A comparative study is shown among some of the questions provided in the questionnaire w.r.t. driving information provided by DS. Out of the 36 questions included in the questionnaire, we will focus in the 9 presented in Table III.

Drivers in general do not have a good perception of the number of kilometers they drive per week (Q9). They estimate better the length (Q10) and the type of their trips (Q11) as well as the number of days they drive per week (Q12).

More than 85% of drivers state that they have the same driving skills as they did 10 years ago and that they have not felt any fears or insecurities in this period (Q15). However, 75% of drivers claim in Q14 that they have been involved in at least an accident in the last 10 years. Comparison of the questionnaire values with the number of near crashes ($THW < 0.15s$) detected for each driver does not offer a clear conclusion. Over-speeding analysis (Q17) concludes, for cases in which data is available (sometimes 3G/4G communication with the remote OSM server is lost), that the users' perception is very close to the real one, except for the D18 that exceeds the allowed speed, although slightly, in 10% of the driving time.

Perception of the ahead safety distance (Q25) is more optimistic than that measured by DS through the car following events, even taking into account these events only are activated for $THW < 0.3s$. Perception of night driving (Q27) is also unrealistic since users drive more time at night than what they actually claim.

Finally, 55% of the users in Q29 claim driving calmly (always or usually) and only 15% consider that it does not (never or rarely). In most cases, driver perception is more optimistic than what is actually measured with DS, although in some cases the opposite occurs. This fact suggests the existence of two kind of drivers: confidence and insecure.

IV. CONCLUSIONS

Results of a NDS for older drivers based on smartphone and our DS app have been presented. Most of them perform calm driving with a tendency to loss the center of the lane and to use the accelerator, the brake and the steering wheel abruptly due to insecurities and distractions. However, there are about 16% of older drivers with aggressive behaviors. Besides, women drive more calmly than men.

The comparative study between drivers questionnaires and DS app shown that most of the user's perceptions regarding

TABLE III

COMPARISON BETWEEN QUESTIONNAIRES [Q] AND DRIVESAFE RESULTS [DS]. Q9. HOW MANY KM DO YOU DRIVE PER WEEK? Q10. HOW LONG ARE YOUR TRIPS? (SHORT [S]/ MEDIAN [M]/ LARGE[L]) Q11. TRIPS TYPE (URBAN [U]/ INTERURBAN [I]/ MIX [M]) Q12. HOW MANY DAYS DO YOU DRIVE PER WEEK? Q14. IN HOW MANY ACCIDENTS HAVE YOU BEEN INVOLVED? Q17. DO YOU DRIVE OVER THE ALLOWED SPEED? (NEVER [N]/ RARELY [R]/ SOMETIMES [S]/ USUALLY [U]/ ALWAYS [A]) Q25. DO YOU KEEP THE AHEAD SECURITY DISTANCE?(NEVER [N]/ RARELY [R]/ SOMETIMES [S]/ USUALLY [U]/ ALWAYS [A]) Q27. DO YOU DRIVE AT NIGHT? (NEVER [N]/ RARELY [R]/ SOMETIMES [S]/ USUALLY [U]/ ALWAYS [A]) Q29. DO YOU DRIVE IN A CLAM WAY? (NEVER [N]/ RARELY [R]/ SOMETIMES [S]/ USUALLY [U]/ ALWAYS [A])

Driver	Q9		Q10		Q11		Q12		Q14		Q17		Q25		Q27		Q29	
	Q	DS	Q	DS	Q	DS	Q	DS	Q	Near crashes	Q	Overs	Q	Carfoll	Q	DS	Q	Behaviour Calm
D1	250	435	S	S	M	-	5	5	1	73	S	-	U	122	R	7,21%	U	90%
D2	250	244	S	S	M	-	6	5	2	2	S	-	S	42	S	25,00%	S	100%
D3	50	36	S	S	M	-	5	4	2	0	R	-	A	0	S	100,00%	S	100%
D4	200	8	S	S	M	-	3	5	2	0	R	-	S	0	R	0,00%	U	100%
D5	150	71	M	S	U	-	7	4	1	2	U	-	R	6	S	16,67%	R	82%
D6	350	149	S	S	M	M	7	7	3	0	S	8,72%	U	4	S	22,22%	S	50%
D7	120	199	S	S	I	-	5	6	1	38	R	-	A	51	S	7,89%	S	76%
D8	300	278	M	S	M	-	6	7	0	2	S	-	U	8	R	36,84%	S	92%
D9	400	173	M	S	I	I	5	5	1	1	S	12%	U	5	S	22,22%	N	75%
D10	320	125	S	S	M	M	5	5	1	6	R	5,18%	U	11	R	14,29%	U	100%
D11	120	4	L	S	M	U	5	3	2	0	R	0%	S	0	S	33,33%	S	100%
D12	150	37	S	S	U	M	7	5	3	0	R	4,21%	U	0	R	25,00%	A	88%
D13	150	104	S	S	M	M	5	7	0	1	S	11,07%	S	17	S	29,63%	A	55%
D14	35	2	S	S	M	U	3	4	2	0	R	1,13%	U	0	R	100,00%	A	100%
D15	100	25	S	S	M	-	5	7	1	8	R	-	S	10	S	0,00%	N	67%
D16	150	95	S	S	M	M	6	4	0	0	R	3,19%	A	0	S	86,67%	A	37%
D17	150	263	M	L	M	M	4	6	0	15	R	5,58%	S	58	S	41,27%	A	80%
D18	50	18	S	S	M	M	3	6	2	1	N	9,29%	S	2	R	0,00%	A	100%
D19	100	186	S	S	U	M	4	4	0	0	S	7,56%	U	24	S	33,33%	A	70%
D20	2500	850	M	L	M	M	6	6	1	2	S	6,71%	U	35	S	0,00%	A	30%

their driving are incorrect and therefore have an unrealistic perception of them. They are not aware of the mistakes they make and unconsciously assimilate an increased risk.

The authors want to emphasize that the sample used in this work is limited and therefore conclusions obtained may not be generalizable. However, results show similar trends to other state of the art studies that validate our study.

As future works we plan to wide the number of users and to include driver clues in the study. Besides we are interesting in programming the app in Android and extend the NDS to other population groups (e.g. young).

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