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Evaluating individual risk proneness with vehicle dynamics and self-report data - toward the efficient detection of At-risk drivers

Blazej Palat[a,*], Guillaume Saint Pierre[b], Patricia Delhomme[c]

[a] The French Institute of Science and Technology for Transport, Development, and Networks (Ifsttar), Planning Mobilities Environment Department, Mobility and Behavior Psychology Lab (Ifsttar-AME/LPC), 25 Allée des Marronniers, F-78000, Versailles-Satory, France

[b] Centre for Studies on Risks, Environment, Mobility and Urban Planning (Cerema), Research Project Team STI, Complexe scientifique de Rangueil, 1 avenue du Colonel Roche, F-31400, Toulouse, France

[c] Ifsttar-AME/LPC, 25 Allée des Marronniers, F-78000, Versailles-Satory, France

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ABSTRACT

Vehicle-dynamics data, now more readily available thanks to moderate-cost, embedded data logging solutions, have been used to study drivers' behavior (acceleration, braking, and yaw rate) through naturalistic driving research aimed at detecting critical safety events. In addition, self-reported measures have been developed to describe these events and to assess various individual risk factors such as sensation seeking, lack of experience, anger expression while driving, and sensitivity to distraction. In the present study, we apply both of these methods of gathering driving data in order to assess risk proneness as accurately as possible. Data were obtained from 131 drivers, who filled in an introductory questionnaire pertaining to their driving habits. Their vehicles were equipped with an external, automatic data-capture device for approximately two months. During that period, the participants reported critical safety events that occurred behind the wheel by (a) pressing a button connected to the device and (b) describing the events in logbooks. They also filled in weekly questionnaires, and at the end of the participation period, a final questionnaire with various self-reported measures pertaining to their driving activity. We processed the data by (a) performing a multiple correspondence analysis of the characteristics assessed via the automatic data capture and self-reports, and (b) categorizing the participants via hierarchical clustering of their coordinates on the dimensions obtained from the correspondence analysis. This allowed us to identify a group of drivers (n = 43) at risk, based on several self-reported measures, in particular, their recent crash involvement, and the frequency of critical acceleration/deceleration events as an objective measure. However, the at-risk drivers did not themselves report more critical safety events than the other two groups.

1. Introduction

Although road crashes generally have multiple causes, it is largely accepted that human factors are one of the most important elements in road-crash causation (Dewar and Olson, 2001; Shinar, 2007). Drivers may be particularly at risk of being involved in a crash if they frequently adopt ill-suited behaviors when behind the wheel. Moreover, risky driving behaviors may be part of larger patterns characterizing driving style (Gregersen and Berg, 1994; Lajunen et al., 1997; Schulze, 1990). Thus, analyzing those patterns can help in identifying at-risk drivers, taking various preventive measures, and training novice drivers to avoid risk-taking as effectively as possible. To make such an analysis meaningful, one has to take into account the specificity of the driving activity, which consists of handling interactions with other road users, sharing the same road space, and especially, time constraints. Other non-negligible factors are different kinds of driving motivations (linked to the purpose of car travel, and the driver's personality and emotions) and factors linked to driving difficulty (for example, road conditions, traffic density, types of infrastructure, etc.) that influence driver performance.

Not exceeding an expected travel time and therefore adjusting one's driving speed are paramount for performing the driving task (Summala, 1997). The difficulty of this task, as perceived in a given situation, is the main factor that constrains speed regulation and determines the threshold of risk awareness (Fuller et al., 2008). Still, for skillful but inexperienced drivers, many risky situations behind the wheel do not seem dangerous at first, so they have to learn to recognize them as such and to take appropriate action. This process gradually leads to the

* Corresponding author.
E-mail addresses: blazej.palat@yahoo.fr (B. Palat), guillaume.saintpierre@cerema.fr (G. Saint Pierre), patricia.delhomme@ifsttar.fr (P. Delhomme).

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development of adaptive behavioral schemes (Fuller, 1984; Näätänen and Summala, 1976), and is probably one of the reasons why young drivers are over-represented in road-crash statistics (Observatoire National Interministeriel de la Sécurité Routière [ONISR], 2016; World Health Organisation [WHO], 2016). However, even experienced drivers can sometimes be surprised by dangerous road interactions and forced to perform emergency maneuvers in order to avoid a crash. It is also not clear to what extent the phenomenon of comparative optimism about the crash risk (perceiving one's own risk level as lower than that of an average driver) actually influences drivers' decision-making (Delhomme, 2000; Delhomme et al., 2009).

Other motives can also make drivers adopt behaviors that increase the risk of being involved in a near miss or in a crash. Driving at high speeds, for instance, can be a source of pleasure (Rothengatter, 1988), especially for thrill-seekers (Jonah, 1997). But driving can also be an unpleasant and stressful experience, especially in some circumstances, such as heavy traffic, difficulty passing, and unfamiliar roads (Gulian et al., 1989; Matthews et al., 1998; Shinar, 1998). Other emotional factors include anger in response to various driving situations, which triggers aggressive reactions (Deffenbacher et al., 2007; for France, see Villieux and Delhomme, 2008). In the context of commuting to work in a car, it has been observed that longer commute times are positively associated to the risk of a crash, perhaps due to increased exposure to fatigue and to the negative emotional experiences mentioned above (Kofi Adanu et al., 2017). Electronic devices such as mobile phones distract drivers' attention and create a mental overload, thus increasing reaction time and the probability of error (Feng et al., 2014; World Health Organization [WHO], 2011). Finally, some common medical conditions, particularly sight problems are recognized as problematic for driving safety (Parker et al., 2003).

By contrast, we can distinguish several factors that impede risky decision-making and/or increase driver alertness, such as being a parent of a small child (Taubman-Ben-Ari and Noy, 2011) or driving with passengers (Delhomme, 1994; Dingus et al., 2016; Porter and Berry, 2001). However, under certain circumstances, driving with a passenger can also have quite opposite effects, insofar as passengers may be a source of distraction (Feng et al., 2014; Maasalo et al., 2017).

Various self-reported measures have been developed to assess driver characteristics likely to be directly or indirectly linked to risky driving behaviors. More recently, some very promising, more objective new risk-assessment methods have been developed based on data collected through vehicle-control systems (like bus CAN[1]; for further information see Di Natale et al., 2012) or by means of independent data-logging systems with embedded sensors (e.g., Dogan, 2010) or smartphone applications (Orfila et al., 2015; Vlassenroot et al., 2015). These data reflect the vehicle's dynamics, i.e., acceleration/deceleration values, thereby enabling the identification of critical safety events or near misses (Bagdadi and Várhelyi, 2011, 2013) by means of kinematic signatures predictive of crash and near-crash risks (Guo and Fang, 2013), and pointing out particular difficulties that drivers encounter. Various approaches have been developed to identify safety-related events using dynamic vehicle data, including extreme value methods (Songchitruksa and Tarko, 2006), counterfactual approaches (Davis et al., 2008), probabilistic approaches (Saunier and Sayed, 2008), or more recent approaches using the discrete Fourier transform (Kluger et al., 2016). However, in most cases, event identification requires (a) selecting a kinematic threshold deemed to represent a "signature" of an avoidance maneuver, and (b) a validation step generally based on confirmatory video analysis. Events detected using such methods can be used as crash surrogates and alternative measures of safety (Dingus et al., 2006; Guo et al., 2010). Naturalistic driving studies (Dingus et al., 2015) and large scale, operational field tests (Malta et al., 2012) have made use of such surrogate measures to evaluate the safety impact of driving behavior or advanced driving-assistance systems. Apart from large-scale assessments of this impact, critical safety events can be used for individual risk assessment (Wu et al., 2014). Moreover, high-risk drivers can be identified using demographic, personality, and driving-characteristic data (Guo and Fang, 2013).

These methods are currently being evaluated and their performance measured using available naturalistic data sets (Perez et al., 2017), but the question remains open as to whether the use of critical safety events can be validated as an efficient surrogate measure of driving risk at both the large-scale and individual levels. The main idea of the present work is to conduct an experiment to collect both self-reported data and automatically captured information about critical safety events. Driver's declarations can be considered as the baseline for assessing the performance of state-of-the-art algorithms and determining potential improvements.

The present study explores the relationships between driver characteristics measured with self-reports, and risk indexes obtained from an automatic data-capture system implemented as a part of a naturalistic driving study. This approach has two aims. One is to analyze driving behavior from the standpoint of risk proneness; the other is to compare the risk-factor information obtained from self-reports and automatic data capture, in order to evaluate the validity of these two methods of gathering information pertaining to road-crash risk by examining whether their use allows us to draw congruent conclusions. Our study was founded by MAIF Foundation, an independent organization supporting scientific research on risk prevention for MAIF[2], a French mutual insurance company.

2. Method

2.1. Participants

The sample consisted of 131 motorists[3] (52.7% males) from Ile-de-France region, averaging 39.7 years of age (σ = 13.74, range 23–77), who volunteered to take part in the study. They were recruited from six driver populations differing in age (19–30, 31–50, and over 50) and gender (see Table 1). They had their car driver's license for 19.2 (σ = 13.14, range 3–49) years on average, and had driven a car for an annual average of 16,606 km (σ = 8828.23, range 1,000–60,000).

2.2. Data collection

Research based on data collected from large car fleets is not straightforward due to the complexity of the data-collection process. The present work relied on a moderate-cost data-collection process that allowed us to make several countermeasures and to take a number of precautions aimed at minimizing the risk of not collecting enough data to draw valid conclusions. We collected data from the car with separate sensors and via an OBD-II connection. In addition, we asked drivers to manually report any critical safety event, and to also use a red button to flag each event in the data set.

Data were obtained from an external, automatic data-capture system powered through the on-board diagnostic (OBD) port, three questionnaires, and a logbook used to gather self-reports about risky driving situations and driver characteristics.

[1] Controller Area Network.

[2] Mutuelle Assurance des Instituteurs de France.

[3] Among the 179 drivers who initiated their participation, 25 did not do all of the expected tasks. They dropped out, either because of technical problems (the data-capture module or its attachment was incompatible with the model of their vehicle, causing interference with on-board electronic devices and/or car-battery overcharge, etc.) or for (other) unknown reasons. Finally, because of device failures, automatically captured data was available only for 131 of the 154 drivers who completed all of the tasks.

Table 1
Number of participants, by age group and gender.

	[19–30]	[31–50]	Over 50	Total
Male	31	27	11	69
Female	22	27	13	62
Total	53	54	24	131

2.2.1. Automatic data-capture device

The device was built for the specific needs of this study by the Superior Technology School of Quebec (LASSENA Team). Three different sensors are embedded in a 86 × 69 x 54 mm black case (see Fig. 1a): an inertial sensor, a GPS, and an OBD-II reader. It is worth noting that the OBD-II connection was needed for powering the logging device, but it was also designed to read information from the vehicle's embedded sensors. The main purpose was to enable continuous logging of vehicle dynamics, so that in case of failure of the logging device's embedded sensors, it remained possible to replace missing signals with the ones collected from the OBD-II. This approach was not successful due to the diversity of the participants' vehicles and the absence of available data for most of them.

Critical safety events were reported manually by the participants, but for a more quantitative approach, they were also asked to "mark" these events using a critical-safety-event button connected to the device via a 1.5 m-long cable. Unfortunately, the quality of this button was insufficient for such a lengthy experiment, and the researchers experienced too many recording issues to be confident enough to use this information.

To ensure the highest scientific standards for this study we chose not to use the unreliable data and to keep only the information recorded by the dedicated sensors (GPS and inertial sensor) or reported by the drivers (logbook). These various precautions enabled us to avoid any detrimental impact on the results.

The device records data from its embedded sensors in binary form at a 16GB micro-SD card with a theoretical capacity of 2,000 h. It draws power from an internal battery that recharges through the connection to the OBD-II port. The power can be turned on or off via a switch placed on the top of the device. However, the device automatically goes into standby mode after 2–5 minutes of inactivity of the vehicle (for example, in a parking lot) and resumes when the embedded accelerometer detects movement. A program converting binary files to CSV files (a format that can subsequently be read, for instance, by data-analysis software) is stored on the card. The device is fixed to the dashboard of the vehicle with an anti-slip pad (see Fig. 1b). The device is not suitable for vehicles manufactured before 2009.

Several measures are logged by the device (see Table 2), encrypted, stored on an internal SD card, and uploaded onto a work station for further processing at the end of the experiment.

The raw data collected during the experiment were then quality checked, merged, and processed using signal-processing algorithms, in order to obtain reliable signals to be tested by the near-miss identification algorithms. For comparison purposes, the algorithms used to identify near misses (Table 3[4]) were derived from recent literature published by Virginia Tech Transportation Institute researchers (VTTI): the 100-car experiment (Dingus et al., 2006) and the SHRP2 program (Wu and Jovanis, 2013).

2.2.2. Self-report measures

2.2.2.1. Four self-report instruments were developed for the study. Introductory questionnaire. Participants reported their age, gender, information about the vehicle they drive the most often, and their driving habits such as annual kilometrage, motives for using their car, and the frequency of car trips.

Weekly questionnaire. Participants reported how many kilometers they had driven for different purposes during the past week, and whether other individuals had driven the car in which the data capture system was installed. If so, the participants stated who had driven the car and for what time period so that the data corresponding to users other than the participant could be identified and eliminated. They also reported whether any important potentially unsetting events occurred during that week.

Logbook. Here, the participant described the critical safety event and its various contextual details, such as the time and date of occurrence of the near miss, the type of infrastructure where it occurred, the speed at which he/she was driving at that moment, how the situation was resolved so as not to result in a crash, what categories of road users were involved, the weather conditions, whether the participant felt angry about the situation or was under the influence of other prior stressful events, how familiar he/she was with the route, whether there were passengers in his/her car, what the motive for the trip was, and when the near-miss happened within the trip (shortly after the beginning, in the middle, close to the end, etc.). This information helped the researchers to evaluate the severity of the event, i.e., the extent to which the situation could have ended in a crash.

- *Final questionnaire.* This questionnaire contained various measures of driver characteristics and past driving experiences. For most questions, the participants responded on five-point Likert scales ranging from low to high levels of frequency or agreement. The measures included:
- Comparative judgment of the risk of being involved in a crash (Delhomme et al., 2009): the participants rated the extent to which they felt at risk of being involved in a crash behind the wheel within the next three years. The same risk was rated with respect to other drivers. The ratings of one's own risk were subtracted from the ratings of others' risk to form comparative indexes, which were positive if the driver rated him/herself as being at a lower risk of being involved in a crash, and negative values if he/she rated him/herself as being at a higher risk.

Table 2
Measures logged by the device built for the study.

Data types	Unit	Size (bits)	Refreshing frequency (Hz)	Kbytes/h
Raw accelerometer measures X, Y & Z	g	48	50	1080
Raw gyroscope measures X, Y & Z	dps	48	50	1080
Raw magnetometer measures X, Y & Z	Gs	48	50	1080
Gyroscope temperature	°C	16	50	360
Inertial data count	/0,005s	32	50	720
Quaternion (W, X, Y, Z)	SU	128	50	2880
GPS week time	ms	32	2	28.8
GPS week number		16	2	14.4
Fix type		8	2	7.2
Number of satellites		8	2	7.2
Latitude	deg	32	2	28.8
Longitude	deg	32	2	28.8
Altitude over ellipsoïd	mm	32	2	28.8
Horizontal precision estimate	mm	32	2	28.8
Vertical precision estimate	mm	32	2	28.8
GPS ground speed	cm/s	32	2	28.8
Heading	deg	32	2	28.8
Speed precision estimation	cm/s	32	2	28.8
Heading precision estimation	deg	32	2	28.8
Total				7516.8

[4] Additionally, the yaw-rate and lateral-acceleration algorithms were tested on the data, but the results obtained from these measures were not used in the present study because of their low variance.

Fig. 1. (a) Automatic data-capture device and (b) its attachment to a car dashboard.

Table 3
Near-miss algorithms used for the study, derived from the VTTI algorithms used during the 100-car and SHRP2 studies.

Trigger type	Description
Longitudinal acceleration	Level of longitudinal deceleration less than or equal to -0.65 g ● Multiple triggers within a 2-s window are combined in the same epoch
Longitudinal jerk	Derivative of longitudinal acceleration less than −1.0 g/s for 1000 ms when the vehicle is travelling at 5 m/s (~18 km/h) or at a higher speed

- Proneness to distraction behind the wheel (scale adapted from Feng et al., 2014).
- Driving anger expression inventory (DAX; Deffenbacher et al., 2007, adapted to French by Villieux and Delhomme, 2008).
- Driver's sensation-seeking scale (Taubman et al., 1996, cited in Yagil, 2001, adapted to French by Delhomme, 2002).
- Mean difference between the most common speed limits and habitual speeds on the roads where these limits are posted. The participants reported the speed at which they usually drove when the speed limit was 30, 50, 70, 90, 110 and 130 km/h. For each speed limit, the difference between the speed reported and the authorized speed was calculated. Finally, for each participant, a mean difference was calculated.
- Number of crashes during the three years prior to the study.
- Number of points[5] on one's driver's license lost during the three years prior to the study.
- Annual kilometrage
- Approximate average time passed behind the wheel per day (in minutes).
- Having at least one minor child living in one's household (yes-no question).
- Having sight problems or not (yes-no question).
- Whether the participant used the vehicle in which the automatic data-capture device was installed to commute to work or not (yes-no question).

2.3. Procedure

The study was approved by the ethics committee of Ifsttar and was registered at the French National Commission on Informatics and Liberty.[6] Data was gathered between the end of March 2015 and mid-December 2016. Every motorist participated for about two months. The participants were recruited in successive waves including 10–40 individuals. For the participants who were willing to come to the study site by their own means, individual sessions with the researchers took place on the premises of the institute that was conducting the research. For the other participants, appointments were made for meeting at a place of their convenience (in most cases close to home or workplace). All participants were paid 50 €.

2.3.1. Initial contact

First, representatives of the insurance company that financed the study established a targeted population of vehicle-insurance policyholders from the Ile-de-France region, selected from the company's client database on the basis of the inclusion criteria (being between 19 and 80 years old and driving a vehicle manufactured after 2008). The policyholders were sorted into six groups according to their gender and age (19–30, 31–50, and over 50). Next the representatives contacted drivers at random in each of the six groups on the telephone and asked them whether they were driving their vehicle at least three times a week and whether they were interested in taking part in a study involving automatic data capture and self-reports of critical safety events. Lists of 10 volunteers from each of the six groups were then sent to the researchers.

2.3.2. First appointment

The researchers called the drivers who had previously said they were interested in participating, in order to schedule the first appointment. However, a certain number of these volunteers never answered the researchers' call. For those who did answer, the researchers explained all of the tasks that the participants were expected to accomplish. At this stage, several of these motorists decided not to participate after all because they found the research too time-consuming or because they were afraid that their insurance company would learn too much about the way they drove even though the researchers stressed the fact that the study was confidential, that the data was collected only for research purposes, and that it would not be revealed to the insurer. Moreover, the researchers also explained that the data would be processed anonymously and analyzed only for the sample as a whole. The drivers who confirmed their initial commitment scheduled an appointment with the researchers and were sent the introductory questionnaire to be filled in and returned before the face-to-face appointment. During this appointment, a researcher redefined the notion of near miss to the participant, as follows: "A near miss is an unexpected

[5] France has a demerit point system wherein drivers begin with a number of points on their license and then lose a variable number of these points every time they are ticketed for a driving violation (the number of points lost depends on the type of violation). When drivers have no points left on their license, they have to take their driving test again. As long as they have at least one point left, they can recover all the points, provided that they drive for three years without being ticketed. At any time before that, they can recover their points by following a rehabilitation training course.

[6] Commission Nationale de l'Informatique et des Libertés (CNIL).

interaction with the infrastructure or with other road users that could have ended in a crash due to the lack of an appropriate reaction". The participant was also told how to recognize a near miss and was given some logbooks. The weekly questionnaire was emailed to the participants shortly after the appointment had ended. Finally, the researcher installed an automatic data-capture module in the participant's vehicle and told the participant how to use the device. For the successive waves of participant recruitment, the researchers asked the insurer for lists of volunteers belonging to age and gender groups that were under-represented in the current sample.

2.3.3. Participation period and final appointment

During the participation period, every time a near miss occurred while the participant was behind the wheel, he/she had to push the critical-safety-event button as soon as the danger was over. Then, after arriving at his/her destination, he/she had to fill in a logbook about the event.

The participant had to fill in the weekly questionnaire and send it to the researchers on Sunday or Monday morning (whether near-misses occurred during the past week or not), unless the participant had not used the car during the past week. Whenever this happened, the participation period was extended by the number of weeks during which the car had not been driven by the participant. Finally, toward the end of the participation period, the participant was recontacted in order to schedule the final appointment, during which he/she filled in the final questionnaire while the researcher took back the logbooks and the automatic data-capture device.

3. Results

We used two statistical procedures to identify relationships between the self-reports and the measures obtained from automatic data capture. First we performed a hierarchical clustering of the drivers according to their individual coordinates on the dimensions obtained from a multiple correspondence analysis of their characteristics (measured using both data-collecting methods). This approach made it possible to examine the extent to which groups of drivers had congruent profiles. Then, following the conclusions of the first analysis, we regressed the most relevant risk-proneness indicator, that is the number of critical acceleration events on a summary indicator of the self-reported driver characteristics. This indicator was represented by the drivers' individual coordinates on the first dimension obtained from a multiple correspondence analysis of their self-reported characteristics.

3.1. Clustering of the drivers

Bearing in mind that the variables were of different types (ordinal ranks, counts, and categories) and that there was a possibility that non-linear relationships existed between them, we converted all of the variables into categorical ones (see Table 4 for the cutoffs) based on the density distribution of each variable. We then conducted a multiple correspondence analysis followed by hierarchical clustering of the individuals' coordinates. As a result, we obtained several groups of drivers sharing common characteristics.

In the preliminary multiple correspondence analysis, the variables indicating whether the driver used his/her vehicle for commuting to work, the number of kilometers driven per year, and verbal expressions of anger (DAX subscale) were identified as outliers (having absolute coordinates greater than 1). In the subsequent analysis, these variables were treated as supplementary variables. Four axes explaining 30.3% of the inertia were retained in the final solution. This relatively low percentage shows how great the variability of the drivers' characteristics was within the sample. We cut the dendrogram of the hierarchical clustering of the participants' individual coordinates on the dimensions obtained from the multiple correspondence analysis at a height of 3.35 (see Fig. 2) in order to obtain a limited number of groups and thereby make the grouping easier to interpret. This approach yielded three groups of drivers (for a summary of the group characteristics, see Table 5). In the following paragraphs, we describe each group by citing the frequencies of variable levels that were significantly different in that group, from those in the entire sample of drivers (see Appendix for a detailed description of these differences).

3.1.1. Group 1 – relaxed and rather careful (n = 46)

Group 1 contained many elderly drivers (30% older than 50, vs. 18% of the entire sample) and mostly females (74% vs. 47% of the entire sample). These drivers were cautious ones who rarely reported speeding (76% reported Level 1 of the mean difference between the speed limit and their actual speed vs. 35% of the entire sample, 22% reported Level 2 vs. 34%, and 2% reported Level 3 vs. 31%). Many had lost few points on their driver's license (Level 1: 61% vs. 49% of the entire sample, Level 2: 39% vs. 51%), and reported few near misses (65% versus 53% for Level 1, 35% vs. 47% for Level 2). Compared to the entire sample, they were neither thrill-seekers (Level 1: 50% vs. 23%, Level 3: 9% vs. 34%) nor very prone to distraction behind the wheel (Level 1: 65% vs. 34%, Level 2: 17% vs. 29%, Level 3: 17% vs. 37%). They rarely expressed anger verbally behind the wheel (Level 1: 39% vs. 21%, Level 3: 15% vs. 34%), rarely used their vehicle to express anger (Level 1: 83% vs. 52%, Level 2: 17% vs. 48%), and quite often used strategies to cope with anger constructively (Level 1: 2% vs. 15%, Level 2: 15% vs. 27%, Level 4: 63% vs. 33%).

3.1.2. Group 2 – pragmatic (n = 42)

The majority of the Group-2 drivers were between 31 and 50 years old (64% vs. 41% of the entire sample), often had one or more minor children living in their household (55% vs. 37% of the entire sample), and were male (69% vs. 53% of the entire sample). Compared to the entire sample, they generally spent the smallest amount of time behind the wheel (Level 1: 45% vs. 30%, Level 4: 5% vs. 19%). Few had sight problems (50% had no sight problems versus 35% of the entire sample). They had rarely been involved in a crash (Level 1: 79% vs. 64%, Level 2: 21% vs. 36%) and had a low frequency of critical acceleration events (Level 1: 69% vs. 47%, Level 3: 10% vs. 23%). However, they reported moderate speeding (Level 1: 17% vs. 35% of the entire sample, Level 2: 60% vs. 34%), proneness to distraction (Level 1: 17% vs. 34%, Level 2: 60% vs. 29%, Level 3: 24% vs. 37%), and relatively frequent use of their vehicle to express anger behind the wheel (Level 1: 38% vs. 52%, Level 2: 62% vs. 48%).

3.1.3. Group 3 – reckless (n = 43)

The drivers in Group 3 were mainly young under 30 years old (67% vs. 40% of the entire sample), and male (65% vs. 53% of the entire sample), had no minors living in their household (77% vs. 63% of the entire sample), and spent quite a long time behind the wheel every day (Level 1: 14% vs. 30%, Level 2: 44% vs. 29%). A relatively large proportion of them reported having sight problems (77% vs. 65% of the entire sample). They often reported blatant disregard of speed limits (Level 1: 9% vs. 35% of the entire sample, Level 3: 67% vs. 31%), had quite a high crash-involvement level (Level 1: 47% vs. 64%, Level 2: 53% vs. 36%), and had lost points on their driver's license (Level 1: 35% vs. 49%, Level 2: 65% vs. 51%). Their relatively high frequency of critical acceleration events (Level 1: 14% vs. 47%, Level 2: 44% vs. 30%, Level 3: 42% vs. 23%) is consistent with this risky profile. Compared to the entire sample, there were quite a few sensation-seekers (Level 1: 5% vs. 23%, Level 3: 60% vs. 34%) and drivers who were prone to distraction (Level 1: 19% vs. 34%, Level 2: 12% vs. 29%, Level 3: 70% vs. 37%) in this group. In addition, they reported using their vehicle to express anger quite frequently (Level 1: 33% vs. 52%, Level 2: 67% vs. 48%).

Table 4
Cutoffs used in the conversion of continuous variables into categorical ones.

Measures Pertaining to…	*Variable Name*	*Categorical-Variable Code*	*Categorical-Variable Level*	*Continuous-Variable Range*
Accidentology	Crash involvement as a Driver[a,b]	accid_nrP100cat	1	0–0.0006
			2	0.0007–0.01
	Number of points lost on one's driver's License[a,b]	perd_pts_totaP100cat	1	0–0.0006
			2	0.0007–0.04
Near misses	Critical acceleration events[a]	ACCP100cat	1	0–0.99
			2	1–2.72
			3	2.73–10.45
	Jerks[a]	JERKP100cat	1	0–9.78
			2	9.79–53.87
	Self-reported critical safety events[a,c]	nincdeclP100cat	1	0–0.08
			2	0.09–1.44
Driving activity	Annual kilometrage	kilo_anCAT	1	1,000–13,500
			2	13,501–20,000
			3	20,001–60,000
	Average daily time spent behind the wheel (in minutes)	tmps_jourCAT	1	6–50
			2	51–80
			3	81–100
			4	101–420
	Mean difference between speed limit and actual speed (km/h)	VITcat	1	−6.04–2.08
			2	2.09–5.83
			3	5.84–15
Psychological characteristics	Driver sensation-seeking	SENSATIONScat	1	1–1.43
			2	1.44–2
			3	2.01–3.71
	Proneness to distraction behind the wheel	SENS_DISTRAcat	1	1–1.77
			2	1.78–2.23
			3	2.24–3.85
	Comparative judgment of risk	JGMT_RISQcat	1	−2–0
			2	0.01–4
DAX	Adaptive/constructive expression of driving anger	DAX_ACEcat	1	1.33–2.13
			2	2.14–2.8
			3	2.81–3.13
			4	3.14–4.6
	Using one's vehicle to express anger	DAX_UVEAcat	1	1–1.55
			2	1.56–3.18
	Aggressive verbal expression of anger	DAX_VAEcat	1	1–1.75
			2	1.76–2.58
			3	2.59–4.58

[a] Per 100 km driven.
[b] During the three years prior to participation in the study.
[c] Before the quantitative analysis, a researcher read all the recovered logbooks in order to eliminate any events that could not be regarded as near misses (not severe enough or not in line with the definition). In case of doubt, the decision to eliminate an event or not was discussed with another researcher. In the end, out of a total of 413 reported events, 31 were not taken into account in further analyses.

3.2. Testing the relationship between self-reported driver characteristics and the number of critical acceleration events

First, we performed a multiple correspondence analysis that included the same categorized variables as in Section 3.1 except jerks and critical acceleration events, so as to obtain a summary indicator of self-reported driver characteristics as represented by the drivers' coordinates on the first axis of the solution (see Table 6 for the coordinates of the self-reported driver-characteristic levels). In order to improve the percentage of inertia explained by this axis, we applied an advanced computation method that involved fitting the off-diagonal submatrices of the Burt matrix by rescaling the solution. Thanks to this approach, the first axis explained 39.2% of the total inertia of the self-reported driver characteristics. Then, we regressed the number of critical acceleration events as a continuous variable over the summary indicator of the self-reported driver characteristics. We can see in Fig. 3 that the summary indicator of the self-reported driver characteristics was significantly and negatively related to the number of critical acceleration events ($b = -1.21$, $p < 0.01$). Since the characteristics associated with risky driving are negatively correlated with this axis (see Table 6), we contend that the riskier the driver, the greater the number of critical acceleration events he/she is involved in.

4. Discussion

We measured driver characteristics using two research methods: automatic data capture and self-reports. Then we categorized the drivers using an exploratory statistical technique – hierarchical clustering of the individual coordinates on the dimensions obtained from a multiple correspondence analysis of the drivers' characteristics – in order to identify drivers the most at risk of being involved in a road crash. This procedure distinguished three groups of drivers, one (Group 3: Reckless) that had several characteristics of risky drivers (previously identified in the literature), such as being a young male (Nell, 2002), a sensation-seeker (Cestac et al., 2011; Whissell and Bigelow, 2003), easily distracted behind the wheel (Feng et al., 2014), etc. This group can also be considered at risk on the basis of their own self-reported crash involvement and points lost on their driver's license. Most importantly, this group also had a high frequency of critical acceleration events, which, in line with prior knowledge, suggests that this indicator is a valid surrogate measure of risky driving. As such, it could therefore be used as a means of increasing the effectiveness of risky- driver detection in experimental studies, but also as a time-varying, driving-risk indicator useful for longitudinal studies. The relationship between this indicator and a summary indicator of the self-reported driver characteristics was further tested and confirmed by a regression analysis.

The indicator based on critical acceleration events seems all the

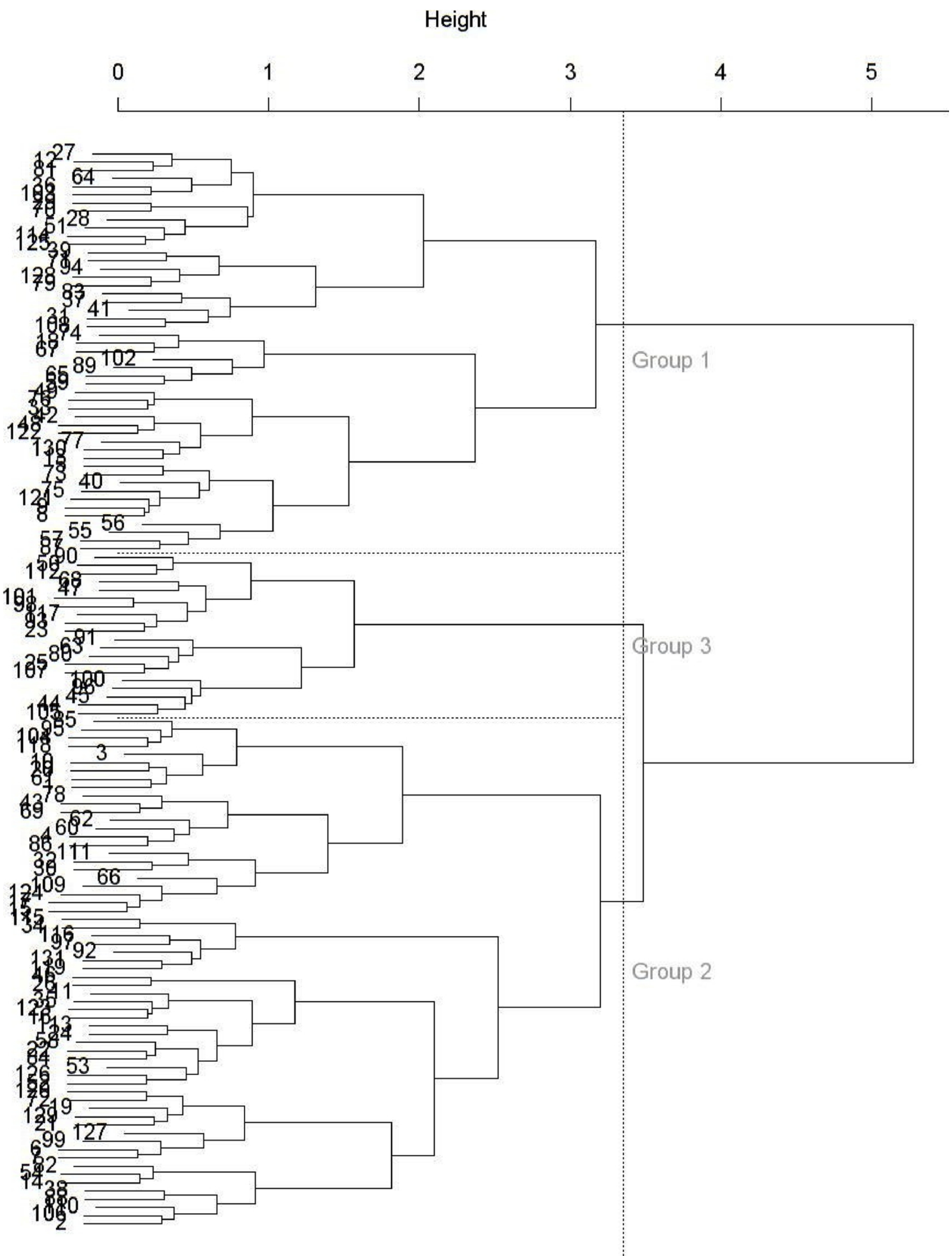

Fig. 2. Dendrogram of the hierarchical clustering of the participants' individual coordinates on the dimensions obtained from multiple correspondence analysis.

more useful because even though they had a high frequency of critical acceleration events, drivers from Group 3 (Reckless) had a similar frequency of self-reported critical safety events to those of the other groups, a fact that can be interpreted as a lack of awareness of risks in this group of drivers. This result shows the extent to which the perception of the riskiness of a driving situation is subjective. We can expect that objectively risky situations may be trivialized by road users, and inversely, that objectively harmless ones may make them overreact. From this standpoint, valid, objective indicators of risk level are particularly informative. Although they do not reflect the risk level directly (which is what self-reports are intended to do), they can reveal either an aggressive driving style, characterized by impetuous accelerations and decelerations, or failure to adapt one's driving behavior to the road environment or traffic conditions (emergency reactions). Still, given that we can deduce from the hierarchical model of driver's behavioral adaptation (Summala, 1997) and learn from research on driving styles (Taubman-Ben-Ari et al., 2016), both those phenomena may very well be directly related to the risk of a crash.

However, our results are not totally clear-cut. Group 1 (Relaxed and Rather Careful) which stood out from the other two on several driving-behavior and near-miss measures (smaller number of points lost on driver's license, fewer self-reported critical safety events, lower speeds, little driver sensation-seeking, less prone to distraction, less anger expression behind the wheel, and more frequent use of adaptive/constructive strategies aimed at calming down) did not report lower crash involvement or a smaller frequency of critical acceleration events than the other two groups.

Furthermore, Group 2 (Pragmatic), in contrast to Group 3 (Reckless) due to its lesser self-reported crash involvement and smaller number of critical acceleration events, displayed several negative driving behaviors, such as moderate speeding, moderate proneness to distraction, and the same frequency of using one's vehicle to express anger as Group 3. Differences between Group 1 and Group 2 can be attributed to gender and age, in that older drivers are probably more involved in accidents

Table 5
Characteristics of the three groups of drivers, identified with hierarchical clustering of their coordinates on the dimensions obtained from multiple correspondence analysis. Categories that were significantly more frequent in a given group are marked with a "+"; ones that were less frequent with a "-". All differences were significant at p < .05 (v-test).

Measures Pertaining to…	*Variable*	*Categorical-Variable Level*	*Group 1: Relaxed and Rather Careful*	*Group2: Pragmatic*	*Group 3: Reckless*
Accidentology	Crash involvment as a driver[a,b]	1		+	–
		2		–	+
	Number of points lost on one's driver's license[a,b]	1	+		–
		2	–		+
Near misses	Critical acceleration events[a]	1		+	–
		2			+
		3		–	+
	Jerks[a]	1			
		2			
	Self-reported critical safety events[a]	1	+		
		2	–		
Driving activity	Annual kilometrage	1			
		2			
		3			
	Average daily time spent behind the wheel	1		+	–
		2			+
		3			
		4		–	
	Mean difference between speed limit and actual speed	1	+	–	–
		2	–	+	
		3	–		+
Psychological characteristics	Driver sensation-seeking	1	+	–	–
		2			
		3	–		+
	Proneness to distraction behind the wheel	1	+	–	–
		2	–	+	–
		3	–	–	+
	Comparative judgment of risk	1			
		2			
DAX	Adaptive/constructive expression of driving anger	1	–		+
		2	–		
		3			
		4	+	–	
	Using one's vehicle to express anger	1	+	–	–
		2	–	+	+
	Aggressive verbal expression of anger	1	+	–	
		2			
		3	–		
Demographic characteristics	Age	19–30	–		+
		31–50		+	–
		50 +	+	–	
	Sight problems	0		+	–
		1		–	+
	Gender	F	+	–	–
		M	–	+	+
	Using the vehicle to commute to work	0			
		1			
	Having at least one minor child in the household	0		–	+
		1		+	–

[a] Per 100 km driven.
[b] During the three years prior to participation in the study.

Table 6
Coordinates of variable levels on the first axis of the multiple correspondence analysis of the self-reported driver characteristics.

Variable Level	Coordinate	Squared Correlation	Contribution
SENSATIONScat:1	0.27	0.65	0.1
VITcat:1	0.24	0.56	0.11
DAX_VAEcat:1	0.2	0.37	NA
DAX_ACEcat:4	0.2	0.64	0.08
SENS_DISTRAcat:1	0.18	0.57	0.07
motif_trav01:0	0.17	0.14	NA
ageFA:50 +	0.16	0.28	0.03
DAX_UVEAcat:1	0.15	0.69	0.07
sexe:F	0.12	0.54	0.04
perd_pts_totaP100cat:1	0.09	0.46	0.02
ageFA:31-50	0.06	0.09	0.01
tmps_jourCAT:1	0.06	0.1	0.01
tmps_jourCAT:4	0.05	0.06	0
JGMT_RISQcat:2	0.05	0.19	0.01
nincdeclP100cat:1	0.04	0.13	0.01
accid_nrP100cat:1	0.02	0.06	0
probl_vue01:1	0.02	0.06	0
jeun_enf:1	0.01	0	0
SENSATIONScat:2	0.01	0	0
jeun_enf:0	−0.01	0	0
tmps_jourCAT:2	−0.02	0.02	0
kilo_anCAT:2	−0.03	0.01	NA
DAX_ACEcat:3	−0.03	0.02	0
VITcat:2	−0.03	0.03	0
kilo_anCAT:3	−0.04	0.01	NA
accid_nrP100cat:2	−0.04	0.06	0
probl_vue01:0	−0.04	0.06	0
DAX_VAEcat:2	−0.04	0.1	NA
JGMT_RISQcat:1	−0.04	0.19	0.01
nincdeclP100cat:2	−0.05	0.13	0.01
SENS_DISTRAcat:2	−0.06	0.09	0.01
kilo_anCAT:1	−0.07	0.15	NA
DAX_ACEcat:2	−0.08	0.19	0.01
perd_pts_totaP100cat:2	−0.08	0.46	0.02
motif_trav01:1	−0.1	0.14	NA
sexe:H	−0.1	0.54	0.03
tmps_jourCAT:3	−0.11	0.21	0.01
SENS_DISTRAcat:3	−0.12	0.38	0.03
ageFA:19-30	−0.13	0.44	0.04
DAX_UVEAcat:2	−0.16	0.69	0.07
SENSATIONScat:3	−0.19	0.57	0.07
DAX_VAEcat:3	−0.2	0.41	NA
VITcat:3	−0.24	0.22	0.1
DAX_ACEcat:1	−0.24	0.53	0.05

without being responsible and female drivers are more likely to declare near misses. These inconsistent results call for further research aimed at evaluating the predictive value of several self-reported tools for evaluating risk proneness.

The greater frequency of sight problems in Group 3 could also account for the higher number of critical acceleration events and self-reported crashes in this group than in Group 2. Nonetheless, speeding behavior provides a far more plausible explanation of the differences between these two groups. The results for Group 3 confirm previous findings (Whissell and Bigelow, 2003) showing that sensation-seeking is a strong predictor of dangerous driving behavior.

From the practical standpoint, the detection of critical acceleration events, which were associated here with self-reported crash involvement, appears to be a promising, easy-to-use tool for evaluating individual risk proneness. In particular, even if identifying safe drivers based on the frequency of critical acceleration events was not really effective in our study, the detection of risky drivers using this method can be considered as quite successful. This measure can be used as a self-evaluation tool for novices as well as experienced car drivers. Coupled with geo-tracking, it can also serve as an indicator of potentially dangerous zones to be identified within road infrastructures.

As concerns the limits of this study, the use of self-reported near-misses may be problematic because of subjectivity in the participants'

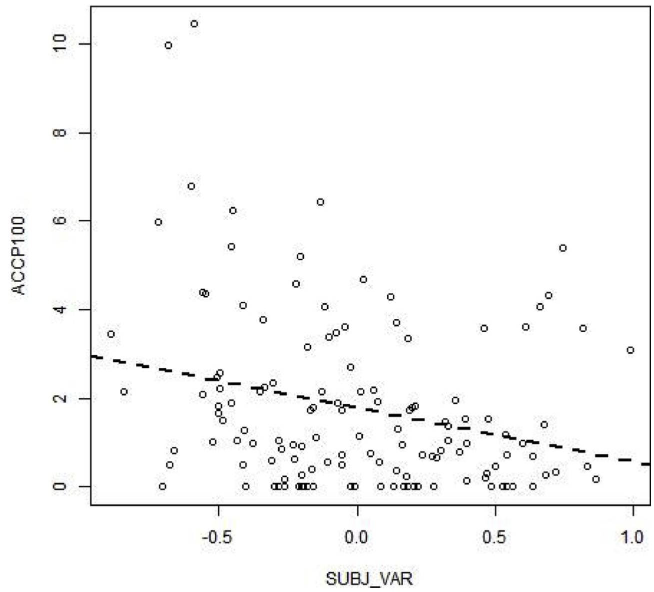

Fig. 3. Scatter plot of the summary indicator of the self-reported driver characteristics (SUBJ_VAR) and the number of critical acceleration events per 100 km (ACCP100). The regression line is shown as a dashed line ($R^2 = 0.07$, $F(1,129) = 9.35$, $p < 0.01$).

perception of risk. For this reason, the participants were asked to describe the events as soon as possible after their occurrence, and in detail, so that we could assess their validity before the near misses were taken into account in the analysis. This approach may still not allow us to rule out subjective influences on the reports of critical safety events, as suggested by some of the results discussed earlier in this section. Another point concerns the possibility of generalizing the results. Insofar as our study sample originated from a highly urbanized region of France, we think it is legitimate to contend that the results can be generalized to urban French car drivers, but not necessarily to drivers from rural areas. Finally, we believe that further research should focus on proposing and validating new surrogate measures of road safety. There is a controversy about the relevance of computing the mean difference between the most common speed limits and habitual speeds. It has been suggested that instead of using equal weights (i.e., a simple average amount over the limit), one could better represent the driving risk using different weights linked to relative differences, or to changes in road safety assessed using the power model (Elvik, 2009; Elvik et al., 2004). Such weights allow for a better representation of speeding in urban areas, where the risk of hitting a pedestrian is greater than in a similar situation on motorways, for example. Using different weights according to the infrastructure type may produce more reliable surrogate measures of safety, both for subjective and objective speed data, and thus deserves further investigation. In future studies, we propose to compare the safety-related event frequency indicators proposed in this paper, with power-model-based weighted speeds, as objective measures of the individual driving risk. We also plan to work with a larger sample of drivers in order to achieve more statistical power.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aap.2018.11.016.

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