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From phone use to speeding and driving under influence: Identifying clusters of driving risk behaviors as an opportunity for targeted interventions

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A R T I C L E I N F O

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A B S T R A C T

Identifying the profile of risky behaviors among drivers is central to propose effective interventions. Due to the multidimensional and overlapping aspects of risky driving behaviors, cluster analysis can provide additional insights in order to identify specific subgroups of risk. This study aimed to identify clusters of driving risk behavior (DRB) among car drivers, and to verify intra-cluster differences concerning clinical and sociodemographic variables. We approached a total of 12,231 drivers and we included 6392 car drivers. A cluster algorithm was used to identify groups of car drivers in relation to the DRB: driving without a seat belt (SB), exceeding the speed limit (SPD), using a cell phone while driving (CELL), and driving after drinking alcohol (DUI).

The algorithm classified drivers within five different DRB profiles. In cluster 1 (20.1%), subjects with a history of CELL. In cluster 2 (41.4%), drivers presented no DRB. In cluster 3 (9.3%), all drivers presented SPD. In cluster 4 (12.5%), drivers presented all DRB. In cluster 5 (16.6%), all drivers presented DUI. Clusters with DUI-related offenses (4 and 5) comprised more men (81.9 and 78.8%, respectively) than the overall sample (63.4%), with more binge drinking (50.9 and 45.7%) and drug use in the previous year (13.5 and 8.6%). Cluster 1 had a high years of education (14.4 $\pm$ 3.4) and the highest personal income (Md = 3000 IQR [2000–5000]). Cluster 2 had older drivers (46.6 $\pm$ 15), and fewer bingers (10.9%). Cluster 4 had the youngest drivers (34.4 $\pm$ 11.4) of all groups. Besides reinforcing previous literature data, our study identified five unprecedented clusters with different profiles of drivers regarding DRB. We identified an original and heterogeneous group of drivers with only CELL misuse, as well as other significant differences among clusters. Hence, our findings show that targeted interventions must be developed for each subgroup in order to effectively produce safe behavior in traffic.

1. Introduction

According to the latest Global Status Report on Road Safety, the number of road traffic deaths has reached 1.35 million individuals in 2016, and is now the worldwide leading cause of death for children and young adults aged 5–29 years (World Health Organization - WHO, 2019). I

T is well established that most road traffic injuries are consequences of human factors, particularly those related to driving behaviors, such as driving above the speed limit and driving under the influence of

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psychoactive substances. As for other behavioral problems, investigating the profile of offenders is considered one of the fundamental approaches to develop effective interventions. Therefore, several studies have investigated the profile of traffic offenders using different types of samples and methodologies (Brown et al., 2016; Dotta-Panichi et al., 2013; Owen et al., 2019).

In general, studies reveal that risk drivers worldwide are mostly male and young, with a high proportion presenting psychiatric disorders and/or alcohol-related problems (Gueye et al., 2019; Owen et al., 2019; Park and Wu, 2019). However, these characteristics alone seem to be insufficient to predict the multiple types of risk behaviors in traffic (Brown et al., 2009; Freeman et al., 2011). More than that, evidence suggests that there are heterogeneous groups among risky drivers, and that different combinations of risk behaviors may be associated with different profiles of drivers (Brown et al., 2016; Dotta-Panichi et al., 2013). A study with a driving simulator, for example, recruited four different groups in relation to risky driving behaviors: driving while impaired recidivists, non-alcohol reckless drivers, low-risk control drivers, and drivers with mixed risk driving profile (Brown et al., 2016).

Although there has been an increase in knowledge about the different driver profiles, there has been almost no improvement in traffic statistics in recent years, especially in low- and middle-income countries – where traffic deaths and injuries present greater significance (World Health Organization - WHO, 2019). Also, most studies have only recruited male participants, even though it is well described that risky driving behaviors are significantly different between genders (Sullman et al., 2017; Wayne and Miller, 2018). Finally, studies usually used theory-driven approaches with few criteria to intentionally assign participants to groups.

Due to the fact that traffic behavior is a multifactorial component with non-linear relationships between different variables, the use of complex methods of analysis based on Machine Learning could be useful to identify patterns of risks that are difficult to recognize when using traditional methods. Among these methods, cluster analysis is a clinically relevant approach, since it identifies inter-individual differences and the existence of multiple groups, avoiding an unidimensional classification (Bora et al., 2016; Burdick et al., 2016). Thus, the use of this kind of analysis favors the identification of the clusters of drivers who present different and overlapping patterns of risky behaviors, hopefully facilitating the development of more specific and effective interventions.

In this study we aimed at identifying clusters of driving risk behavior in a Brazilian sample of drivers using a machine learning algorithm and verifying their differences concerning characteristics that were previously associated with traffic offenders, such as sociodemographic characteristics and drug use profile.

2. Methods

2.1. Participants and data sampling

Our data were collected as part of the Global Road Safety Program Brazil/*Vida no Trânsito* project (Hyder and Bishai, 2012; Peden, 2010). This study comprised three different arms: (i) Roadside survey - interview of drivers at Brazilian roadblocks in highways in order to measure risk behaviors, especially alcohol/drug use and speed; (ii) KAP survey - interview of drivers at public places to understand their knowledge, attitudes and practices (KAP) concerning alcohol/drug use and other behavioral risk factors; (iii) Speed measures - analysis of speed of vehicles in Brazilian roads and its association with road characteristics.

We analyzed data from the KAP survey study, which was conducted in five Brazilian cities: Belo Horizonte, Campo Grande, Curitiba, Palmas, and Teresina. In October and November 2013, the investigators piloted the KAP survey in Teresina and Palmas, respectively. After revisions, the methods and instruments were applied in all five intervention cities once between March and May 2014, and again between August and November 2014. While the survey was explicitly designed to better understand drunk driving, questions regarding other risk behaviors were also embedded.

The sampling occurred in two stages:

1. Intervention cities were divided into regions along existing municipal divisions. The regions were selected with the assumption that the distribution of drivers therein was equal to that of the general (city-wide) driving population. The number of regions that were sampled varied according to the size of the intervention city.
2. For each region, data collection teams identified sites in which they could safely approach drivers. Consistent with methods employed in other Global Road Safety Program countries, these sites included supermarkets, gas stations, shopping malls, fairs, plazas, and public parks (Bachani et al., 2013). Where needed, the team requested authorization from business owners to conduct the surveys in parking lots or near the entrances/exits of a given establishment. The same data collection sites were maintained for all rounds.

The target population for the KAP survey consisted of drivers registered in each intervention city. Anyone reporting not having driven in the last 12 months, or being a tourist, or being from another city, was excluded. Individuals under 18 years were also excluded. KAP surveys were conducted via face-to-face interviews, and all data were entered into a structured questionnaire based on Open Data Kit (ODK), which was accessed via tablet (Hartung et al., 2010). Data were collected during five consecutive days, by two different teams, between 4:00 and 10:00 p.m. - although adjustments were made due to the specificities of each city (e.g. climatic conditions). Data collection teams consisted of four interviewers and a manager, who in addition to overseeing the data collection process also provided a brief intervention to drivers who reported drinking immediately prior to the interview, especially if they reported intending to drive after the interview. This intervention consisted of explaining the risks associated with drunk driving and offering the possibility of a safe ride to the participant's home via a friend or family member, or a taxi voucher. A total of 12,231 drivers were approached during the KAP survey. Of those, 1308 reported not having driven in the previous 12 months, and 1199 refused to participate, yieldinga final sample of 9724 participants.

This study was approved by the ethical committee of the Hospital de Clínicas de Porto Alegre. All subjects included in the study signed the informed consent. The investigation was carried out in accordance with the latest version of the Declaration of Helsinki.

2.2. Data preprocessing

For the present analysis, we selected only the participants who referred being car or truck drivers ($n = 7439$). From those, we excluded 1045 participants who did not complete the interview, and for that reason presented missing information. Therefore, a total of 6392 drivers were included in the present analysis.

The risk behavior variables used to perform the cluster analysis were preprocessed and dichotomized (further Supplemental Methods S1).

2.3. Data analysis

We used the Partition Around Medoids (PAM) algorithm to identify clusters of car drivers in relation to behavior risk, using as input the variables presented in the previous section (Schubert and Rousseeuw, 2018). Compared to the classical partitioning algorithm *k-means*, PAM is more robust to noise and outliers because this machine learning technique attempts to minimize the sum of dissimilarities between data points labeled to be in a cluster and its medoid (Park and Jun 2009). We used the Gower's distance method to analyze the dissimilarities between pairs of data points (Akay and Yüksel, 2018). The best number of clusters was determined analyzing the average silhouette width and the practical interpretation of the clusters. Other internal clustering validation measures such as Dunn and Gamma Indexes were performed to verify the quality of clustering results (Hassani and Seidl, 2017).

The clustering analysis was implemented in R scripts using RStudio and the packages cluster, fpc, factoextra. The remaining analyses were performed using IBM SPSS(SPSS Inc. Released, 2009; Version 18.0). Data are presented as mean and standard deviation for symmetric continuous variables, as quartiles for asymmetric continuous variables, and as absolute and relative frequencies for categorical variables. We tested for statistical differences between clusters regarding socio-demographic and other variables using analysis of variance (ANOVA) with post-hoc Tukey's HSD test for multiple comparisons, and Z-test for differences in proportions with Bonferroni adjustment. Results are presented using APA-style subscripts letters with 99% confidence level.

3. Results

3.1. Sample profile

Descriptive statistics of the 6392 car drivers interviewed can be found in Table 1. Drivers were mostly men, with a mean age of 42 years and with a monthly income of R$ 3000.00 (approximately USD 1200). The most prevalent driving offense reported by drivers was using a cellphone while driving (38.2%), followed by driving after drinking alcohol (27.6%). However, even with the high prevalence of traffic offenses, most drivers reported not receiving traffic fines in the previous year. Regarding their beliefs, most drivers said they were conscious about the risks of the evaluated behaviors.

3.2. Cluster analysis

Our clustering method resulted in a partition of five distinct clusters, which reached average Silhouette widths equal to 0.65, Dunn index equal to 0.71, and Person-gamma index of 0.78. The Silhouette indicates how well objects are clustered. Dunn index means the ratio between compactness within a cluster and separation between clusters. Person-gamma index basically computes concordant and discordant pairs of objects (Tomasini et al., 2017). All of those quality measures range from −1 (poorly) to 1 (well clustered).

In the first cluster, all participants (n = 1,282, 20.1%) presented a history of cell phone use while driving. We refer to it as the CELL cluster. The second cluster (n = 2,649, 41.4%) was composed of subjects who did not present driving risk behaviors, except for a very low prevalence of driving without a seat belt, we called the Low-Risk group. In the third cluster (n = 595, 9.3%) all drivers presented a history of exceeding the speed limit - therefore, it was named the Speeders cluster. In the fourth cluster (n = 802, 12.5%), called the High-Risk, drivers presented a high prevalence of all driving risk behaviors. Finally, the fifth cluster (n = 1,064, 16.6%) was composed of individuals with a history of driving after drinking alcohol, and with a low prevalence of other driving risk behaviors. It was named the driving under the influence (DUI) cluster. Fig. 1 shows the composition of each cluster by the variables used to generate them.

3.3. Sociodemographic characteristics, drug use, driving experiences, and beliefs among clusters

Table 2 shows the sociodemographic characteristics, alcohol/psychoactive substances-related variables, and of history of fines of each cluster.

The CELL cluster presented more years of education than all other groups and, along with the Low-Risk cluster, records the highest proportion of women concerning the overall sample. The CELL also showed, along with the High-Risk cluster, the highest percentage of drivers who did not believe cell phones impaired their driving skills. Besides, it showed the highest frequency of subjects fined for cell phone use while driving in the previous year.

The Low-Risk cluster showed the highest mean age and the most substantial proportion of drivers aware of impairment in driving due to alcohol and cell phone use (90.8 and 98.6% respectively). Regarding the Speeders cluster, it had the lowest personal income. Furthermore, the Speeders did not show gender differences compared to the general sample.

The High-Risk cluster has the youngest group of drive, displays the highest prevalence of road traffic crashes after drinking alcohol in a lifetime, and also of illicit drug use in the previous year. It was also the most fined cluster for speeding and for not wearing a seat belt while driving. The High-Risk, along with the DUI cluster, presented the highest proportion of men, of frequent binge drinkers, and of driving after illicit drug use. Also, the High-Risk cluster showed the lowest percentage of drivers that did not believe alcohol consumption impacts driving performance. The DUI cluster was the most similar to the High-Risk cluster. In contrast, the Low-Risk cluster was different concerning all compared variables.

Finally, the proportion of driving years in life (the ratio between total years of driving experience and age) was homogeneous across all clusters.

Table 1
Descriptive statistics for all 6392 drivers in the sample.

Driving risk behaviours variables	
Driving without seat belt [a]	990 (15.5)
Exceeding the speed limit [a]	1756 (27.5)
Using phone while driving [a]	2,440 (38.2)
Driving after drinking alcohol [a]	1767 (27.6)
Sociodemographics variables	
Sex [a]	
Male	4053 (63.4)
Female	2339 (36.6)
Age (years) [b]	42.3 ± 14.4
Years of Education [b]	13.4 ± 3.7
Monthly income (unit of R$1000.00) [3]	3,0 [1,5 - 5,0]
Proportion of driving years in life (%) [b]	42.3 ± 20.3
Substance and driving related variables	
Binge drink [a]	
Often binge drink	1438 (22.5)
Don't binge drink	2278 (35.6)
Don't drink	2676 (41.9)
Ilicit drug use [a,c]	485 (7.6)
Drove after ilicit drug use [a,c,d]	249 (51.3)
Believes alcohol impair driving [a]	5278 (82.6)
Believes cellphone use impair driving [a]	6090 (95.3)
Fined for cellphone use while driving [a,c]	351 (5.5)
Fined for not seat belt use while driving [a,c]	269 (4.2)
Fined for speeding [a,c]	1205 (18.9)
Had a RTC after drink alcohol, lifetime [a]	347 (5.4)

[a] Frequency (%).
[b] Mean ± standard deviation or [3]Median [1st-3rd Quartiles].
[c] In last year. RTC = Road traffic crash.
[d] Answered only by the 485 participants who reported had used ilicit drugs in the past year.

4. Discussion

Our study suggests that risky behaviors are quite prevalent in this sample. In line with previous evidence, the results show that there are heterogeneous subgroups of drivers that engage in different risky driving behaviors. Specifically, the cluster analysis identified five groups of drivers that differed both on sociodemographic characteristics and drug use profile. To the best of our knowledge, this is the first paper that performs such analysis using unsupervised machine learning from a large sample of Brazilian drivers, and suggests that the CELL drivers might be seen as a different cluster with its own specificities.

In our study, the CELL cluster presented the highest proportion of women, with subjects reporting the highest levels of education among

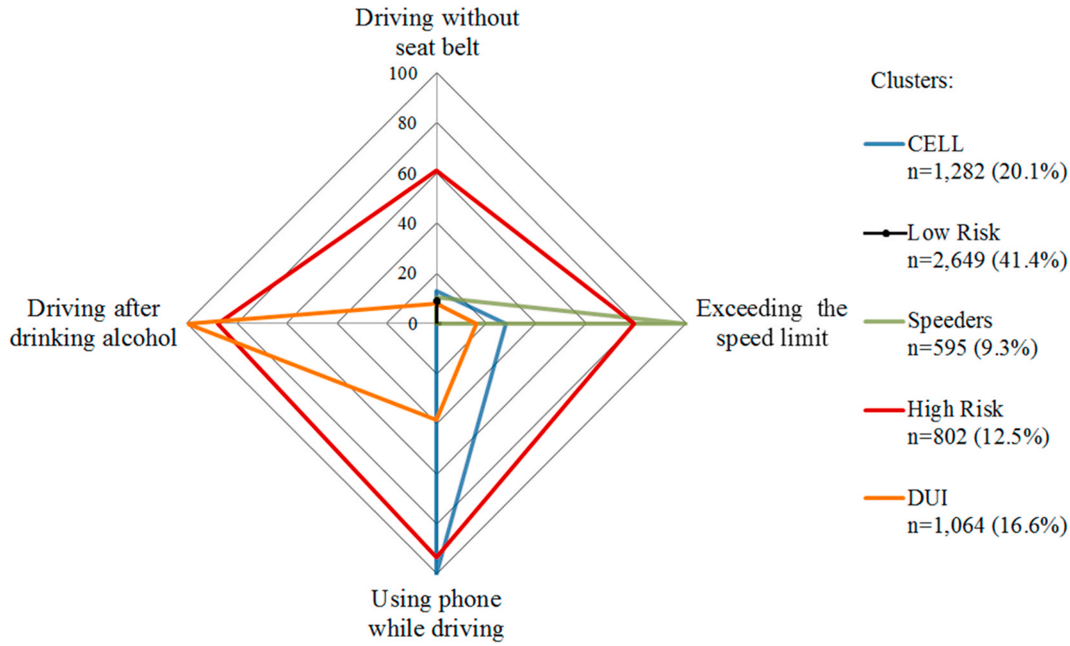

Fig. 1. Prevalence of driving risk behaviors among clusters.

Table 2
Sociodemographic characteristics, substance and driving related variables of each cluster.

	C1 - CELL		C2 - Low Risk		C3 - Speeders		C4 - High Risk		C5 - DUI	
	n = 1282 (20.1%)		n = 2649 (41.4%)		n = 595 (9.3%)		n = 802 (12.5%)		n = 1064 (16.6%)	
Sociodemographics variables										
Sex [a]										
Male	714 (55.7)	a	1446 (54.6)	a	398 (66.9)	b	657 (81.9)	c	838 (78.8)	c
Female	568 (44.3)		1203 (45.4)		197 (33.1)		145 (18.1)		226 (21.2)	
Age (years) [b]	39.8 ± 12.5	a	46.6 ± 15.0	b	43 ± 15.4	c	34.4 ± 11.4	d	40.5 ± 12.7	a
Years of Education [b]	14.4 ± 3.4	a	12.8 ± 3.9	b	12.7 ± 3.9	b	13.7 ± 3.2	c	13.8 ± 3.4	c
Monthly income (unit of R$1000.00)[c]	3,0 [2,0–5,0]	a	2,4 [1,4 - 4,0]	b	2,5 [1,5–4,0]	b	3,0 [1,7–5,0]	a	3,0 [2,0–5,5]	a
Proportion of driving years in life (%)[b]	43.2 ± 19.0		41.6 ± 21.9		41.9 ± 21.2		41.1 ± 18.1		43.8 ± 18.6	
Substance and driving related variables										
Binge drink [a]										
Often binge drink	177 (13.8)	a	288 (10.9)	a	79 (13.3)	a	408 (50.9)	b	486 (45.7)	b
Don't binge drink	397 (31.0)	a	823 (31.1)	a	154 (25.9)	a	326 (40.6)	b	578 (54.3)	c
Don't drink	708 (55.2)	a	1538 (58.1)	a	362 (60.8)	a	68 (8.5)	b	0 (0)	–
Ilicit drug use[a,d]	98 (7.6)	a	153 (5.8)	a	35 (5.9)	a	108 (13.5)	b	91 (8.6)	a
Drove after ilicit drug use[a,d,e]	51 (52.0)	a,b	59 (38.6)	a	11 (31.4)	a,c	71 (65.7)	b	57 (62.6)	b,c
Believes alcohol impair driving[a]	1132 (88.3)	a	2405 (90.8)	a	534 (89.7)	a	530 (66.1)	b	677 (63.6)	b
Believes cellphone use impair driving[a]	1157 (90.2)	a	2612 (98.6)	b	585 (98.3)	b,c	717 (89.4)	a	1019 (95.8)	c
Fined for cellphone use while driving[a,d]	152 (11.9)	a	23 (0.9)	b	15 (2.5)	c	99 (12.3)	a	62 (5.8)	c
Fined for not seat belt use while driving[a,d]	61 (4.8)	a	54 (2.0)	b	23 (3.9)	a,b	84 (10.5)	c	47 (4.4)	a
Fined for speeding [a,d]	278 (21.7)	a	282 (10.6)	b	142 (23.9)	a	284 (35.4)	c	219 (20.6)	a
Had a RTC after drink alcohol, lifetime [a]	60 (4.7)	a	66 (2.5)	b	20 (3.4)	a,b	112 (14.0)	c	89 (8.4)	d

[a] Frequency (% within colums), Z-test for proportion difference with Bonferroni method.
[b] Mean ± standard deviation or.
[c] Median [1st-3rd Quartiles], ANOVA with post-hoc Tukey's HSD for multiple comparisons. Same subscript letter across columns indicate no significant difference between cluster's at 99% confidence level.
[d] In last year. RTC = Road traffic crash.
[e] Answered only by the 485 participants who reported had used ilicit drugs in the past year.

the sample. About 27% of the drivers in this group also reported speeding behaviors. Interestingly, no other paper has previously reported a specific group of drivers that presented cell phone use while driving as their most prevalent risk behavior. As far as we know, a profile comparison of these specific groups has not been described yet, concerning other established clusters of risky driving. The behavior of using a cell phone while driving has been described as highly detrimental to driver performance because it decreases vital cognitive skills to drive, such as attention and psychomotor speed (Niu et al., 2019; Stavrinos et al., 2011). A meta-analysis with 977 participants from 28 experimental studies showed that typing and reading text messages while driving adversely affected eye movements, stimulus detection, reaction time, collisions, lane positioning, speed and headway (Caird et al., 2014). In this sense, the use of cell phone seems to increase up to 4-fold the likelihood of crashing independently of gender (Haworth et al., n.d.; McEvoy et al., 2005). One study argued that talking on a cell phone not only diminished the participant's safety of driving, but also diminished their awareness of the safeness of their driving (Sanbonmatsu et al., 2016). In our study, this was observed with a negligible effect. About 90% of drivers inthe CELL cluster reported being aware that cell phone use impairs driving, which was not substantially lower than in the other clusters. This points to a behavior that persists even with the awareness of its danger, causing greater concern for this group. This scenario becomes even more worrying some over the years, given the significant increase in the use of smartphones and the time drivers are exposed to them.

Nowadays, there is a debate over banning cell phones while driving. Places in which laws prohibit cell phone use while driving were effective in reducing long-term behavior of handheld phone use although there was no control of switching devices between hands in this analysis. Furthermore, this result was independent of enforcement intensity and citation (McCartt et al., 2010; Rakauskas et al., 2004). Corroborating this finding, the CELL cluster was the second cluster more fined for cell phone use while driving. Therefore, it seems that fine-based interventions are not enough to cause behavioral changes in drivers. In addition, it might be necessary to apply joint actions, such as continuing education activities in the community, public initiatives and a mass media campaigns directed at cell phone violations. Still, law enforcement could be followed with specific interventions for women who represent the higher proportion in the CELL profile cluster. A group of highly educated women drivers who are distracted while driving and typing – or talking through their cell phones – would benefit from a strategy based on female police officers endorsing rules regarding cell phone use in areas of a high density of crashes due to distracted driving – as well as school drop-off areas – with an approach based on preventing crashes of mothers taking their children to school. In this sense, educational interventions may be effective for young female drivers to change risk behavior as demonstrated in a recent work (Cuttelo et al., 2020).

Some cell phone devices may have a great contribution to law enforcement, preventing drivers to use cell phone while moving, or after reaching a certain speed limit. However, this technology still has some limitations, since the passenger mode can be easily activated by drivers. Still, multimedia panels coupled to the car with a wireless display could prevent cell phone handling by simply activate the call or message by voice command. However, more studies should be done to determine whether a reduced handheld cell phone may avoid road crashes.

In general terms, the Low-Risk cluster did not exhibit any risky driving behavior and showed a high-risk perception of the evaluated behaviors, suggesting a cognitive and behavioral profile more appropriate for driving. One study reported that perceived risk may be associated with precautionary driver behaviors, such as seat belt use and speed reductions, in some cultures but not in others (Şimşekoğlu et al., 2013). The risk perception, however, usually has a positive association with safe driver behaviors, engaging drivers in defensive driving and, consequently, generating less fines (Chaudhary et al., 2004; Şimşekoğlu et al., 2012). The Low-Risk cluster showed less frequency of fines for cell phone use while driving and for no seat belt use while driving. Also, this group comprised older people and a high frequency of women. It has been well described in the literature that older drivers maintain safe driver behavior more often than younger drivers (Simons-Morton et al., 2016). Younger drivers have 2.5 times more accident involvement due to reckless behaviors on trafficthan older drivers (Clarke et al., 2005; Simons-Morton et al., 2011).

In contrast, the high-risk cluster exhibited all driving risk behaviors as well as a high frequency of male gender and young age, corroborating the aforementioned findings. The high-risk drivers were also more fined for cellphone use while driving, for no seat belt use while driving, and for exceeding the speed limit because of its risky behavior pattern. We hypothesize that this cluster could probably be of subjects with sensation-seeking traits, since this kind of personality adopts a risky driving style and has an elevated need to experience novelty, being frequently involved in accidents and receiving fines (Brandau et al., 2011). A study using personality traits with cluster analysis found two groups of high-risk drivers: one of them with high levels of sensation seeking, hostility, and another with high levels of depression and irritability (Deery and Fildes, 1999). Another author also identified two risk clusters (Ulleberg, 2001). The first comprised mostly men with low levels of altruism and high levels of sensation-seeking and irresponsibility, and the second reported high sensation seeking, aggression, anxiety, and driving anger.

Moreover, high-risk drivers had a high frequency of binge drinking and drug use among all clusters. Risky driving is a reflection of other behavioral problems, such as delinquency, aggressive behavior, drug abuse and alcohol abuse (Brandau et al., 2011). Heavy drinking is an important predictor of driving under the influence, because some people with episodes of binge drinking have temporary deficits in decision-making, leading them to misinterpretations about their cognitive skills to drive after drinking (Couture et al., 2008; Gianoulakis et al., 2003; Junghanns et al., 2005). However, there is no consensus about this point (Moan et al., 2013; Yao et al., 2018). In summary, the High-Risk cluster is opposite to the Low-Risk cluster, and may need more integrative interventions in order to prevent relapse, such as psychological and psychiatric evaluations and, individualized assessments for treatment, when necessary.

For High-Risk cluster, it is suggested that areas, based on Kernel density maps, of high alcohol selling and consumption must be approached in a completely different manner. Male bingers and drug users would respond better to highly visible "blitzes" of heavily armed police forces rather than a gentle approach (De Boni et al., 2013). Some Australian provinces have shown deterrent efforts to test alcohol and other drugs in oral fluid, where on site testing has significantly diminished the risk of drunk/drugged driving (Drummer et al., 2012). Some countries are also using Automatic License Plate Recognition, which is an image processing technology that uses a license plate to identify the vehicle (Du et al., 2012). This system may identify hot-list targets of criminals, recidivism DUI offender, unlicensed registered owners, among other infractions. Another sanction commonly applied in most countries is the application of high fines on drink-driving offenders. However, no significant deterrent effects from higher fines have been shown (Weatherburn, 2011).

In line of the evidence earlier cited, the DUI cluster exhibited the second highest frequency of men and of binge drinking. Several evidence suggest that one third of first-time DUI offenders have an alcohol use disorder or other drinking problems, but the frequency is high when drivers are multiple DUI offenders (Okamura et al., 2014; Wickens et al., 2016). A survey with male DUI offenders reported that 26–36% of subjects were alcohol-dependent (Okamura et al., 2014). Several types of interventions were already suggested for DUI offenders. Most interventions are based on recidivism DUI offenders, who are responsible for a substantial proportion of all offenses and are more likely to persist in their DUI behavior than first offenders (Yu, 1995). The use of alcohol ignition interlocks for this population has been tested and is shown to be effective only while installed in the vehicle. Furthermore, rehabilitation programs demonstrate a reduction in DUI recidivism, although there is a better effect when in addition to educational components it includes cognitive behavior therapies (Rider, 2007). The use of victim impact panels has been used as an intervention, with the idea of sensitizing offenders with stories of members who have suffered serious injuries or lost family members as a result of DUI. However, there were no satisfactory results in most of the studies (Miller, 2015; Wheeler, 2004). According to some systematic reviews, it is not possible to make conclusive statements about the types of programs that are likely to be most effective for them (Miller et al., 2015). Nonetheless, there was some evidence to support the effectiveness of intensive supervision programs, which includes multi components factors, such as DUI education, substance use treatment, electronic monitoring, and license sanction and interlocks (DeYoung, 1997; Miller et al., 2015; Strashny, 2013).

Our study endorses the more contemporaneous trend of "slicing the pie" of prevention and enforcement options towards risky driving, against a more "one size fits all"- traditional approach. Regarding

Speeders clusters intervention, it may be suggested cars with a physical speed limiter, which can prevent offenders from reaching excessive and dangerous speeds on the road. Other interventions may be effectively applied for road traffic injury prevention when combined such as speed control measures, educational intervention, enforcement, road improvement, and community programs (Staton et al., 2016).

We understand how distant these approaches are when we consider contacting a high-risk speeder on the road - who wears no seatbelt and uses drugs and alcohol while driving, and who may be intoxicated during the approach. This exemplifies how much effort has to be put in designing suitable interventions for those individuals with characteristics that are quite distant. Also, governmental agencies that lead to the efforts towards implementing enforcement and prevention have great difficulty in applying effective educational interventions – but rather systematic enforcement on the road, on a routine basis, and without previous information as to when and where these will happen – aiming at a deterrence effect. Our clusters show the basis for designing these different – and eventually complementary strategies.

Our study has some limitations, including the cross-sectional design, the reliance on self-reported data, and the use of a convenience sample. Although our sample should not be considered representative of the Brazilian driver population due to the use of non-probabilistic sampling. Nevertheless, we took some precautions were taken to ensure the recruitment places were distributed within different areas of the cities' territory so that the sociodemographic variability between the areas could be somehow considered. Moreover, due to the fact that data collection was made in public places, it lacks information regarding personality and biological variables that could be useful to deepen the investigation of these subgroups of drivers, and to recommend specific interventions. Even though cluster results are usually difficult to replicate, this method is being consistently used to identify clusters of drivers with different profiles in order to provide foundations for public policies. In this sense, we were able to identify important similarities as much as differences between the clusters, which are fundamental in order to propose interventions according to group specificities. On the other hand, this study was the first to offer an evaluation of multiple driving risk behaviors with a large sample of Brazilian drivers, using a non-driven method of group selection.

The identification of clusters of drivers who engage in DRB in different ways is an important strategy to guide traffic policies concerning training, education, prevention and enforcement. The most important conclusion that our data provide is that there is a high heterogeneity of driving risk behaviors among the evaluated sample of drivers, and that this knowledge needs to be taken into consideration when developing and evaluating different strategies and interventions to deter drivers and prevent relapse in risky traffic behaviors. Our results indicate, for example, that female drivers are at lower risk for traffic violations, and that they are mostly associated with cell phone use while driving. Thus, prevention strategies of cell phone use should have a greater focus on this audience. Moreover, unlike what appears in some developed countries research, socioeconomic characteristics presented less practical significance when comparing the different profiles of DRB, perhaps due to the fact that in Brazil car drivers present similar socioeconomic levels. In our sample, psychoactive substance use and abuse seems to be a relevant marker associated with high risk profiles. Therefore, an early identification of drivers who drink in binge, for example, could result in better strategies for the driver licensing process and also driver monitoring. In addition, our results endorse the hypothesis that lower awareness of alcohol and cell phone impairment is associated with higher frequency of DRB (cell phone use while driving and drink driving, respectively). However, all clusters seem to present some levels of awareness, reinforcing the idea that education by itself does not change behavior without enforcement. On this matter, there is still a relevant lack of traffic enforcement in Brazil – which can be corroborated by the low prevalence of reported fines among the clusters with different risk behaviors.

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CRediT authorship contribution statement

Francisco Diego Rabelo-da-Ponte: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing - original draft, Visualization. **Juliana Nichterwitz Scherer:** Conceptualization, Methodology, Investigation, Data curation, Writing - original draft, Project administration. **Vinicius Roglio:** Software, Formal analysis, Data curation, Writing - original draft. **Eduardo Nunes Borges:** Software, Validation, Data curation, Writing - original draft, Supervision. **Tanara Sousa:** Investigation. **Ives Cavalcante Passos:** Writing - review & editing, Supervision. **Lisia von Diemen:** Validation, Resources, Writing - review & editing, Supervision. **Felix Kessler:** Validation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Flavio Pechansky:** Validation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

Ives Cavalcante Passos has received consulting fees from Torrent/Omnifarma. Ives Cavalcante Passos has received research grants from the Brazilian National Research Council (CNPq). The remaining authors do not have competing interests to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpsychires.2020.11.025.

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