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Ageing and Driving Performance in the UK Using Normal Mixture Model Cluster Analysis Technique

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ABSTRACT: This research addresses the issue of an individual's ability to drive and especially of those individuals that are questionably demented (dementia is suspected) or are in a state of very mild dementia and are therefore the most difficult to identify. A methodology has been developed for categorization of drivers by considering three driving performance indices/parameters simultaneously. This novel approach precluded the previous technique whereby only a single driving performance index (an omnibus approach without the ability to discriminate between normal driving behavior and risky driving habits primarily due to cognitive decline) is considered. Driving performance of 28 young and 28 old drivers was gauged by 24 driving performance parameters through two designed drives on driving simulator. Normal Mixture Model Cluster Analysis was used in the performance-based categorization of drivers. It was found that out of a total of 56 drivers, 8 turned out to be "poor drivers". Results from neuropsychological/cognitive tests showed on average lower cognitive performance for the "poor drivers" group. This methodology will preclude the need for measurement of driving skills through driving instructors.

KEYWORDS: Older Drivers; Mild Cognitive Impairment (MCI); Cluster Analysis; Driving Simulation; Driving Performance Index

1. INTRODUCTION

Within the driving population, a considerable proportion is exhibiting decline in cognitive abilities relevant to driving. Fatality risk of older drivers is reported to be around 3 folds that of the middle-aged group (Cheung & McCartt, 2011; Khan et al. 2018). Older healthy drivers perform the driving task at a level that is comparable with healthy young adults. Since dementing illnesses are common in old age, certain proportions of older drivers are in the early stages of a dementing illness or already clinically demented (Khan et al. 2018).

Early stage diagnosis of cognitive decrement is very hard; and since the decline due to normal ageing and due to very early-stage dementia is not readily distinguishable by physicians and so numerous older drivers may continue to drive (Parasuraman & Nestor, 1993; Stinchcombe et al., 2016; Carr & O'Neill, 2015). Incompetence in driving is not exhibited by all persons having early stage dementia (Brown & Ott, 2004). Decisions regarding discontinuation of driving for those having mild dementia are problematic, whereas there is strong consensus that persons having moderate to severe dementia should stop driving (Carter et al., 2015). Therefore, fit driver status can be accorded to some mild dementia-individuals. Thus, it can be acknowledged that screening drivers is not an easy task. The objective of this research was the development and deployment of a methodology by which those drivers who exhibit risky driving behavior, could be identified and especially those drivers having very mild dementia or are questionably demented and are significantly hard to discern. This research focuses on identification of cognitively impaired drivers from cluster analysis.

2. METHODOLOGY

According to Patomella and Kottorp (2005), the usual on-road driving test cannot identify risky driving practices (due to cognitive impairment), as it is not demanding enough. On-road driving evaluation gauged through an index has shown significant Pearson correlation with driving performance on the simulator (Casutt et al., 2014). Henceforth, the STISIM® simulator was selected to achieve the research objectives (Khan et al. 2018).

According to Lee et al. (2002), it is crucial that "controlled processing"/effortful processing rather than "automatic processing" be employed in gauging driving skills through driving simulator scenarios, to differentiate between the driving abilities of normal and cognitively impaired drivers. Automatic processes do not deteriorate with age; these are acquired through practice over many years. Lane keeping, gear changing, and steering etc. constitute automatic processes. The authors further highlight that specific information processing stages be stressed to make the drivers vulnerable to committing errors, by exposing them to hazardous/complex scenarios. In this context, a 21-mile drive (designated as Drive-I) was designed having a duration of 40 minutes with numerous hazardous, unexpected driving scenarios embedded within normal driving routines. To give drivers an idea about the magnitude of their speed, the road alignment was studded with telephone poles at 200 ft spacing beyond the shoulders (Khan, 2009, Khan et al. 2018).

The DA (Divided Attention) and the CF (Car-Following) drive collectively designated as Drive-II, was a 14-mile drive with a total duration of 16 minutes, with about 8 minutes consumed by the DA portion. The first portion of the drive comprised of a DA task while the second portion was a CF task. Due to the workload from competing sources (within the DA and CF drive), it is not possible for the driver to respond in an optimum manner to the primary task (driving) and secondary task (e.g., DA task) and one or both are bound to suffer. This trade-off can be measured and may show up as degraded performance on a variety of driving proficiency parameters, for example, increase in reaction time, nonadherence to lane discipline or speed observance (Khan, 2009, Khan et al. 2018).

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It may be highlighted that in the Main Drive (Drive-I) it was communicated to drivers that: (a) posted speed limit should be followed, (b) low-speed should be avoided i.e., speed not in excess of 5 mph below the speed limit (low speed reminded to drivers through a "ding" sound after every three seconds), (c) the number of low-speed warnings ("ding" sounds) will be recorded. Slow driving (which manifests overcautiousness) has been categorized as a discriminating error by researchers (Staplin et al., 1999; Thompson et al., 2012). Driving skill degradation is signified by discriminating errors that can be categorized as likely dangerous errors (Khan, 2009).

3. SAMPLE OF DRIVERS

A comparative approach was used to gauge decline in driving competence of experienced older and younger drivers by employing a driving simulator; this was because more frequent crashes take place in a simulator compared to real life situations (Martin, 2013). Figure 1 shows the research methodology, wherein all drivers in the sample were to possess 5 years or more experience and a UK driving license having validity. Table 1 illustrates demographic information relevant to the successfully tested candidates (Khan et al. 2018).

Systematic effects of tiredness were side-lined by following a morning-testing-protocol. Each candidate was subjected to a 3-4 minute practice drive prior to the actual simulation test. (Khan et al. 2018). The following neuropsychological testing regime was administered to the 56 candidates in random order:

1. Rey-Osterrieth Test
2. Trail-Making Test
3. Dichotic Test
4. UFOV Test (comprising of ufov1, ufov2 and ufov3)
5. Clock Drawing Test.
6. Paper Folding Test

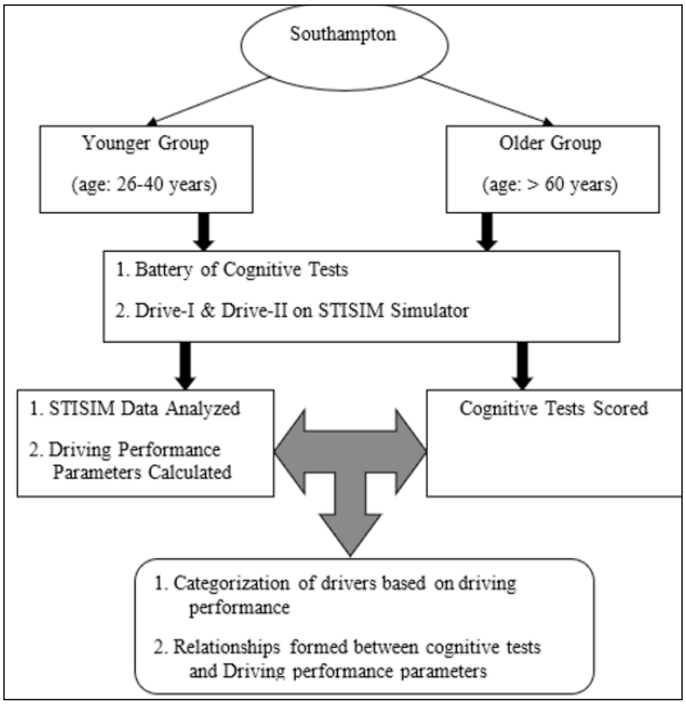

Figure 1. Schematic diagram showing the methodology of research.

A total of 24 different driving performance parameters were collected. These parameters were the following:

1. No. of Total Hazards
2. No. of Low-Speed Warnings
3. Over Speed Limit (Percent of Time)
4. Out of Lane (Percent of Time)
5. Steering Reversal rate (Mountain Drive)
6. Time-To-Line Crossing (Mountain Drive)
7. Absolute Difference in Modulus
8. Delay (Phase Shift)
9. Coherence
10. No. of Correct DA Responses
11. No. of DAs with No Response
12. Reaction Time DA Task
13. Standard Deviation of Reaction Time
14. Reaction Time to Stop Sign
15. Absolute Difference in Speed DA Task
16. Standard Deviation in Speed DA Task
17. Absolute Difference Lane Position DA Task
18. Standard Deviation Lane Position DA Task
19. Absolute Difference Lane position Car-Following Task
20. Standard Deviation Lane position Car-Following Task
21. Steering Reversal Rate DA Task
22. Steering Reversal Rate Car-Following
23. Time-To-Line Crossing DA Task
24. Time-To-Line Crossing Car-Following

The 24 driving performance parameters were relevant to Drive-I and Drive-II. They were chosen because in order to identify drivers exhibiting risky driving behavior due to cognitive impairment, it is necessary that the effects of parameters that assess driving skills at the "controlled processing level" ("effortful" processing) be assessed predominantly. "Effortful" or "controlled processes" are slow, capacity-demanding and are used to deal with unpredictable or unfamiliar stimulus demands. In contrast, "Automatic processes" are fast, involuntary, and place limited demands on attentional capacity. The peculiar design of Drive-I and Drive-II and driving performance evaluation through these 24 driving performance parameters facilitated "controlled processing level" skills to be predominantly assessed.

The 24 different driving performance parameters were generated at a frequency of 20 hertz (i.e. every 0.05 seconds) in ASCII code by STISIM® driving simulator software as an output and this raw data was later further processed/filtered using Microsoft EXCEL® and MATLAB® programming.

4. DEVELOPMENT OF DRIVING PERFORMANCE INDICATORS

Item Analysis and Cronbach's Alpha Reliability Coefficient concepts were used to develop three different driving performance indices. Principal Components Analysis was used to derive the corresponding weighted versions. Cronbach's Alpha Reliability Coefficient along with a weighting procedure was used to remove parameters contributing to "noise". Parameters contributing to "signal" were kept in the calculation of driving performance indices. The following three types of unit nominal weight indices were calculated (Khan et al. 2018).

Group	Females	Males	Total Subjects	Min. Age (yrs)	Max. Age (yrs)	Average Age (yrs)	50th Percentile Age (yrs)	Standard Deviation (SD) age (yrs)
Old	12	16	28	60.3	88.4	68.7	66.2	7.4
Young	14	14	28	26.3	40.0	32.3	32.3	4.4

Table 1. Demographic detail of the successfully-tested younger and older driver groups (Khan et al. 2018).

1. Index named DPI1, a composite of 24 driving performance parameters.
2. Index named DPI2, a composite of all 24 driving performance parameters with the exception of the Number of Total Hazards.
3. Index named DPI3, a composite of the 24 driving performance parameters except for Number of Low-Speed Warnings and Number of Total Hazards.

Slow driving (e.g., overcautiousness) has been categorized as an error which discriminates between drivers (Thompson et al., 2012; Pavlou et al., 2016). Driving skill degradation is signified by discriminating errors that can be categorized as likely dangerous errors (Khan et al. 2018). Differential weights enhance an index's predictive ability (Streiner et al., 2015). DPI3-weighted, DPI1-weighted and DPI2-weighted were the indices that were derived through Principal Component Analysis (Khan et al. 2018).

5. CLUSTER ANALYSIS

Driving performance was differentiated through Normal mixture model cluster analysis (NMMCA) in which certain parameters were used to identify relevant driver groupings/clusters. Owing to a lack of prior knowledge (Hothorn & Everitt, 2014) about parameters relevant to informative cluster analysis/ driver classification, six different performance parameters were adopted/explored (see Table 2).

These six scenarios were carefully synthesized to ensure inclusion of few appropriate variables and the adequate description of observations/objects (Everitt et al., 2011). According to researchers (Lew et al., 2005; Schultheis et al., 2003), values of a performance index (higher score of the index representing better performance) greater than 2 standard deviations below the mean (of the normal group) would classify a driver as "failed". If this model is adopted in a normally distributed population, it would always consider 2.3% (standard normal variable $Z \leq -2$ is 0.023) of the normal drivers as failed drivers irrespective of their performance. Also, the use of a single driving performance measure is an omnibus approach lacking the ability to discriminate between normal drivers and cognitively impaired drivers. A single driving parameter which taps "driver error" has been found to be non-discriminatory with regard to driving performance (Casutt et al., 2014). Since more than one measure was present in most of the six performance parameters, cluster analysis technique was used to categorize drivers based upon performance.

Serial	Scenario
1.	DPI1
2.	DPI1-weighted
3.	DPI2 and Number of Total Hazards
4.	DPI2-weighted and Number of Total Hazards
5.	DPI3, Number of Total Hazards and Number of Low-speed Warnings
6.	DPI3-weighted, Number of Total Hazards and Number of Low-speed Warnings

Table 2. Six alternatives/scenarios used in driver classification.

The groupings arrived through cluster analysis should be rational in context of research objectives since there is no prior information available in defining groupings. The cluster analysis technique of Normal Mixture Modeling (Fraley & Raftery, 2002) as opposed to the older heuristic clustering methods was employed.

MCLUST add-on was used in statistical software package R® (compiled in S programming language) to perform NMMCA (Fraley & Raftery, 2006). Approximate Bayes factors are used for comparison of the different clusters enabling statistical evaluation. Generally, greater values of BIC support cluster models and their numbers. Ill-conditioning can be avoided by adopting lesser number of clusters.

6. RESULTS AND DISCUSSION

Cluster analysis using the six alternatives/scenarios (Table 2) was performed. The driver group possessing poor driving skills identified using the five scenarios (serial 1 through 5 of Table 2) was not viable (relevant to attributes of poor driving skills and number of groups) because these five scenarios resulted in more clusters compared to the total number of drivers.

Cluster analysis using the sixth scenario mentioned in Table 2 resulted in three best models shown in Table 3. Table 3 exhibits the best three models with their BIC values. The 3-cluster group and the 2-cluster group are quite close in terms of BIC values. Henceforth, using sicario 6 of Table 2 the number of clusters was constrained to 3 using NMMCA; Table 4, Table 5, and Figure 2 show the results from this analysis. Table 4 depicts the best three 3-cluster models along with their BIC values using scenario 6 of Table 2. As evident from the table, highest value has been achieved by Model EEV. Table 5 shows the three groups selected along with details on average scores on the three parameters of scenario 6 of Table 2. On average, group 3 has secured the most favorable score (lowest score on number of total hazards, lowest score on number of low-speed warnings, and highest score on DPI3-weighted) on all the three parameters with respect to group 1 and 2. Comparing group 1 and 2, group 1 has more favorable scores than group 2. Hence, driving performance in increasing order of skill is group 2, group 1, and group 3. The poor drivers were categorized in Group 2 and were 8 in number. The same three parameters of Table 5 have been illustrated in driver classification graph as shown in Figure 2(d).

The multivariate versions of the spread (which in fact match the covariances of the components) for each mixture component have been depicted as ellipses in the figure with centers at their means, μ_k (Khan et al. 2018). Judging from Table 5 and the ellipses in Figure 2(d), group No. 2 deviated from the other two groups with regard to the variables under consideration. There was no significant difference between group No. 1 and 3, and as a result they were merged to form the "not-poor-drivers" group consisting of 48 drivers. Group No. 2 was designated as a "poor drivers" group, which consisted of 8 drivers.

Best Bayes Information Criteria (BIC) Values		
VEI,2	EEV,3	VEV,2
-1070.690	-1075.632	-1076.110

Table 3. Best three models along with BIC values and number of groups/clusters using NMMCA for scenario 6 mentioned in Table 2.

Best BIC Values		
VEI,3	EEI,3	EEV,3
-1079.265	-1083.289	-1075.632

Table 4. Best three 3-cluster models along with their BIC values using scenario 6 of Table 2.

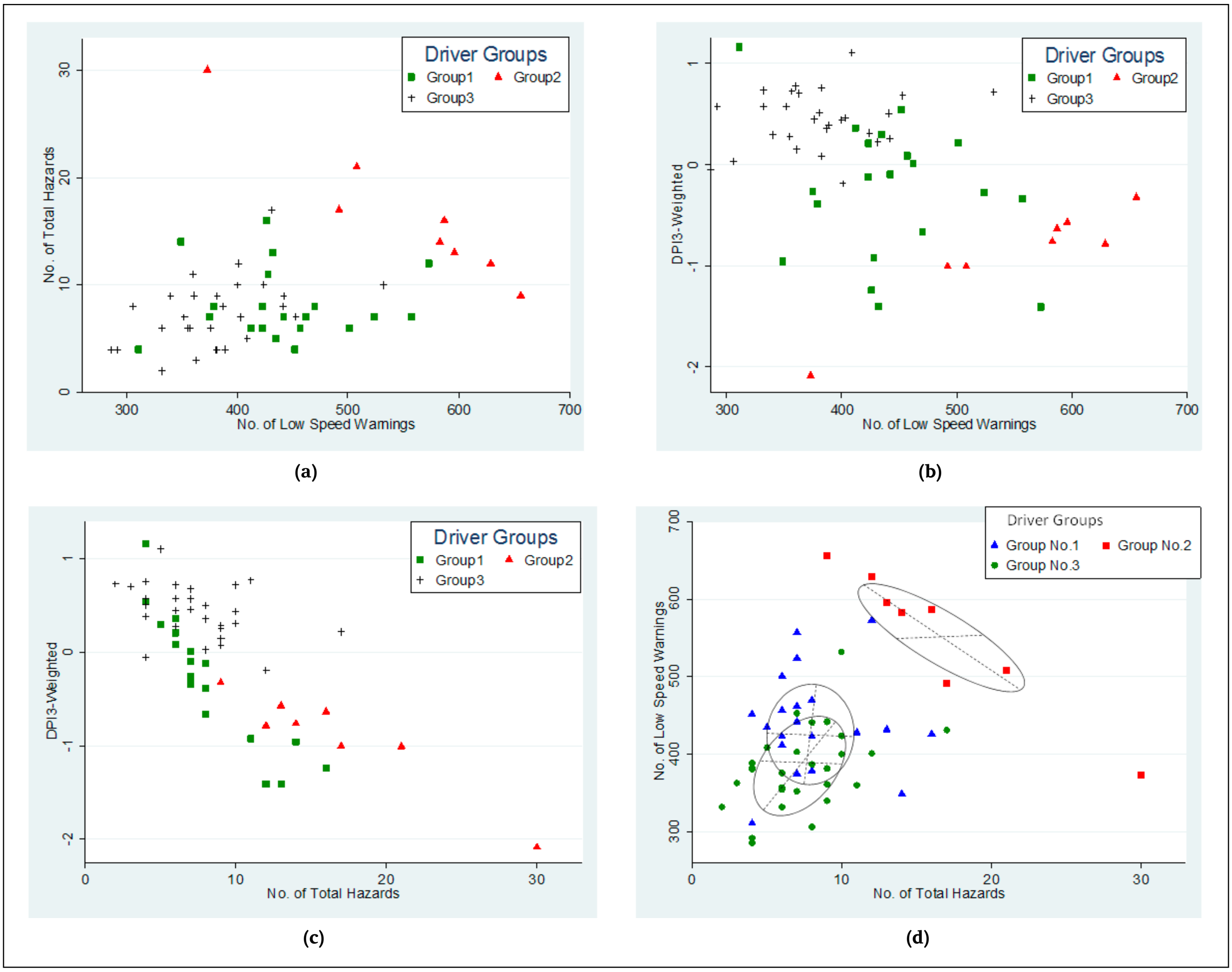

Figure 2 Scatter-matrix plots of the three parameters of scenario 6 of Table 2 using the 3-group/cluster model EEV having BIC of -1075.632.

Scenario 6 of Table 2 with a 3-cluster solution using model EEV provides the most intuitively appropriate and clinically relevant classification, supported by the following points:

- Group 2 was the poor performance group, and comprised of 8 drivers from the old driver group.
- Group 2 had the largest number of accidents despite the fact that they were driving on average at the lowest speeds and had the most unfavorable score on DPI3-weighted.
- The number of clusters advised by the software (2 or 3) was intuitively within the limits.
- On average, group 3 had secured the most favorable score (lowest score on number of total hazards, lowest score on number of low-speed warnings, and highest score on DPI3-weighted) on all the three parameters with respect to group 1 and 2. Comparing group 1 and 2, group 1 had more favorable scores than group 2. Hence, driving performance in increasing order of skill can be attributed as group 2, group 1, and group 3.
- Owing to the small difference in BIC values between the 2-cluster group (BIC= -1070.690) and the 3-cluster group (BIC= -1075.632), selection of the 3-cluster group was logical, and provided the most clinically relevant classification, and is in tune with research (Fraley and Raftery, 2002).
- Results of the neuropsychological tests of the drivers were also used as a guide in evaluating and selecting the clusters obtained from our model.
- Average scores on nine neuropsychological cognitive tests (see Table 6) of the three driver groups (i.e., group 1, 2 and 3) were compared. Favorable scores in increasing order were those of group 2, group 1 and then group 3. Similarly, favorable scores in increasing order on the three parameters of scenario 6 of Table 2 were those of group 2, group 1 and then group 3.

Groups for model EEV with 3 clusters/groups having BIC of -1075.632				
Group No.	Number of Drivers	Mean Number of Low-Speed warnings	Mean Number of Total Hazards	Mean DPI3-weighted
1	20	441.55	8.1	-0.2607223
2	8	553	16.5	-0.8960832
3	28	381.0357	7.321429	0.4422541

Max. & Min. value of Number of Low-Speed warnings = 656, 286
Max. & Min. value of Number of Total Hazards = 30, 2
Max. & Min. value of DPI3-weighted = 1.158719, -2.083781

Table 5. Mean values of scenario 6 for model EEV having BIC of -1075.632.

Our sample also had five “ideal objects” consisted of 3 drivers from the younger group and 2 from the older. The driving skills of these five drivers was well known on account of their

	Trail making test*	Clock drawing test	Rey-Copy test	Rey-Recall test	Dichotic listening test*	Paper folding test	ufov1 test*	ufov2 test*	ufov3 test*
Group No. 1	81.75	14.8	32.05	19.45	1.85	38.47	18.9	31.3	113.45
Group No. 2	114.87	14	29.37	15.93	7	24.75	20.12	86.75	241
Group No. 3	64.78	14.92	33.5	23.82	1.41	52.01	17.10	19.39	75.64

*In this test, greater score shows lower cognitive performance.

Table 6. Neuropsychological Tests showing average scores of the 56 test drivers (Khan et al. 2018).

relationship with the Transportation Research Group of the university. After NMMCA, these drivers were categorized in the most relevant clusters/groups and fitted very well within the model, which is quite in harmony within the guidelines provided by Gordon (1999).

The final selected model (i.e., EEV, having BIC value = -1075.632) based upon scenario 6 of Table 2 had the most intuitively reasonable parameters which were selected based upon sound psychometric principles and incorporated in the design of the simulation drive, keeping in view the driving behavior demonstrated by cognitively impaired drivers.

Group 2 had the largest number of accidents despite driving on average at the lowest speeds and also had the most unfavorable score rating on DPI3-weighted (a parameter of numerous driving performance indicators). In this novel methodology, three variables were simultaneously used in identifying the "poor driver group", which consisted of 8 drivers out of the 56 by using the technique of NMMCA. This methodology will instill confidence in physicians' decisions regarding fitness to drive relevant to questionably demented drivers. And will prove as a supplementary tool to an on-road assessment/evaluation.

One small limitation of this research was that the sample of drivers used in this study was relatively small due to limited resources; however, that did not in any way unfavorably affect the analysis of the study as we were able to sample quite diverse driving behavior from this small sample. Ceiling and floor effects were avoided, as for example, even the most skillful of the drivers had a small number of accidents (Number of Total Hazards) to their credit which proved the discriminatory ability of the drive (the drive being designed based on psychometric principles). Findings from this research may be used to develop improved driving performance models based on neuropsychological/cognitive tests.

7. CONCLUSIONS

The driver group possessing poor driving skills was identified using Normal Mixture Model Cluster Analysis technique by considering simultaneously three different driving performance measures/indices:

- Index representing a substantial risk of crashes and traffic accidents,
- Index representing discriminating errors, and
- A composite index of 22 driving performance parameters.

This novel approach precluded the previous technique whereby only a single driving performance index was considered. The following are our conclusions:

1. The Normal Mixture Model Cluster Analysis technique can be used to identify driver performance groups through the use of multiple driving performance indices simultaneously.
2. In the performance-based driver groups, the "poor drivers" group was found to be a relatively smaller group.
3. Similar to the cluster analysis and driving performance results, scores from neuropsychological / cognitive tests also show on average lower cognitive performance for group 2 i.e., the "poor drivers".

It is noteworthy to mention that since doctors assessing fitness to drive do not have a driving simulator at hand, to facilitate such an assessment, a series of neuropsychological tests was identified in this same study to assess the ability to drive. Driving performance of these same young and older drivers was modeled through multiple linear regression and univariate logistic regression tools using driving performance indices and neuropsychological tests and results reported in Khan et al. (2018) by the same principal researchers.

8. ABBREVIATIONS USED

AIC	Akaike Information Criterion
BIC	Bayes Information Criterion
CF	Car-Following
DA	Divided Attention
DAT	Dementia of the Alzheimer Type
DPI	Driving Performance Index
EM	Expectation Maximization
HC	Hierarchical Clustering
kph	Kilometer per hour
ML	Maximum Likelihood
mph	Miles per hour
NHTSA	National Highway Traffic Safety Administration
NMMCA	Normal Mixture Model Cluster Analysis
PDE	Previously Defined Events
ROC	Receiver Operating Characteristic
SD	Standard Deviation
SDL	Scenario Definition Language
TLC	Time-To-Line Crossing
UFOV	Useful Field of View

9. DATA AVAILABILITY STATEMENT (DAS)

The data that support the findings of this study are openly available in 4TU.ResearchData at http://doi.org/10.4121/19158821, and at http://doi.org/10.4121/19136954.

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