Braking Behavior Profiling of Professional Car Drivers using Instrumented Vehicle Data

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Abstract

In this study, we propose a methodology to identify various braking patterns exhibited by different drivers by means of objective performance data. The driving data was collected in real-time for 15 passenger car drivers without any experimental controls. The driving profiles were segmented into events of braking maneuvers, which are further analyzed using k-means clustering to group the similar patterns. Total four braking patterns were identified, each indicating different aspect of braking behavior. The results showed that individual drivers are differing concerning the proportion of patterns exhibited during the drive period. The associations between the identified patterns and the external influencing factors such as road geometry, traffic conditions, type of lead vehicle, and driver distraction were presented. The study results can be used to provide feedback to driver, and support in improvising the driving efficiency.

Keywords: Driving patterns; Driving profiles; K-means clustering; Real driving data.

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1. Introduction

Driver behavior is observed to be the major contributory factor in road crashes across the world [1]. In this context, the behavioral assessment of drivers is highly needed to assist the drivers for safe travel. Over the last three decades, significant research is conducted on assessing the driving performance in the perspective of safety, comfort, and economy. The research resulted in the expression “driving style”, which indicates the habitual way of driving, including the choices of speed, acceleration, headways, level of attentiveness, calmness while driving, and driving attitudes towards other users [2]. The driver behavior assessment was originated by means of questionnaire surveys where the drivers were evaluated based on the driving errors, violations, attitudes, and personality traits [3,4]. The questionnaire surveys indicate the subjective judgements based on past experiences, which are more prone to reporting bias. Moreover, the questionnaire based driving styles do not refer to the actual faulty behaviors exhibited by drivers.

Some studies considered the kinematic performance, and the derived objective measures to assess driving behavior. The abstract features like maximum, mean and standard deviation of acceleration, speed, and percentage of time speed exceeds speed limit in a trip are used to classify the driving styles [5,6]. However, the aggregated performance does not indicate the safety critical maneuvers executed in the real-time. In this context, few studies evaluated the driving performance based on the frequency of safety critical events performed in the study period. The number of sudden accelerations, sudden decelerations, and sharp turnings observed in a trip are used for characterizing the driver [7,8]. In these studies, the ground truth/reference thresholds used to identify the critical events are not uniform, and varied from one study to another. The threshold based characterization is subjected to the relevance and representation of the chosen threshold values. Very few studies explored the driving profiles without any prior ground truth. In reference [9], the authors clustered the car-following periods of 10-car and 10-truck drivers, and identified 30 patterns. Similarly, the base-line events collected as part of SHRP-2 study were clustered into three different driving styles [10]. In most of the studies, the characterization of driving styles was presented in a holistic manner combining the nature of different driving maneuvers into a single representative driving style [11]. The definitive approach of understanding the behavior in a particular driving regime is less explored.

The traffic conditions in asian countries like India are heterogeneous in nature, and well-known for maintaining shorter headways and poor lane discipline [12]. In this context, braking is considered to be the critical driving operation which is more probable to be associated with road-crashes compared to the other driving tasks. Considering this, the present study aimed to analyze the braking behavior of individuals and the effect of external influencing factors on different behavoral patterns. The continuous driving profiles of 15 professional car drivers are collected by conducting real tests on road. The braking events are extracted from the segmented driving profiles, and characterized by means of the respective speed and acceleration values, reflecting the objective judgements of driver’s driving choices. The event data is analyzed using unsupervised techniques to identify the braking patterns, which are further associated with the exteranl influencing factors related to driving environment.

The next section of the paper details the study methodology, and the third section presents the clustering analysis. The fourth section presents the individual driver behavioural variations. The last section of the paper concludes the work and present future scope.

2. Methodology

The study methodology is depicted in **Figure 1**. The framework for the current study is designed in five steps: 1) Data collection; 2) Braking maneuver extraction; 3) Maneuver clustering & braking pattern characterization; 4) Driver behavior heterogeneity; and 5) Influence of external factors. First, the driving data was collected for passenger car drivers in real-road conditions using high-frequency data loggers. Second, the braking maneuvers and the respective performance features were extracted from the driving profiles. In the third step, the extracted braking maneuvers were clustered using k-means clustering. Based on the cluster characteristics, the pattern classification was assigned to each braking pattern. Fourth, the proportions of different patterns were presented at individual driver-level. In the last step, the proportions of events were computed against each external factor and compared among the braking patterns.

2.1 Data Collection

The data for the present study is collected using an instrumented vehicle over a defined study stretch. The study section is of 23 kilometers length on the four-lane divided national highway (NH-65) near Hyderabad city. The study stretch consists of total 12 intersections, 13 mid-block openings, and four gentle curves. The participants for the study are selected from the fleet management companies surrounding Hyderabad city, who volunteered to participate. Drivers fulfilling the suitability criteria of minimum one year driving experience, no crash history, and familiar with the study route are chosen to participate in the study. The goals of the study are informed to all the participants before commencing the trip, and a declaration of consent was obtained from each participant. The ethical approcal for the study was granted by the Institutional Ethics Committee of Indian Institute of Technology, Hyderabad. For each participant, the data was collected for a minimum of two trips, and was compensated by a gift after the study period.

The study vehicle with the instrumentation details is depicted in **Figure 2**. The passenger car is fitted with a high-frequency GPS instrumentation and four video cameras (Video Vbox-Pro). The instrument captures the video data of four camera views (**Figure 2**) which is synchronized with the respective kinematic and positional data recorded at a frequency of 10 Hz. The data collection is in progress, and in this paper we have considered the driving data of 15 drivers.

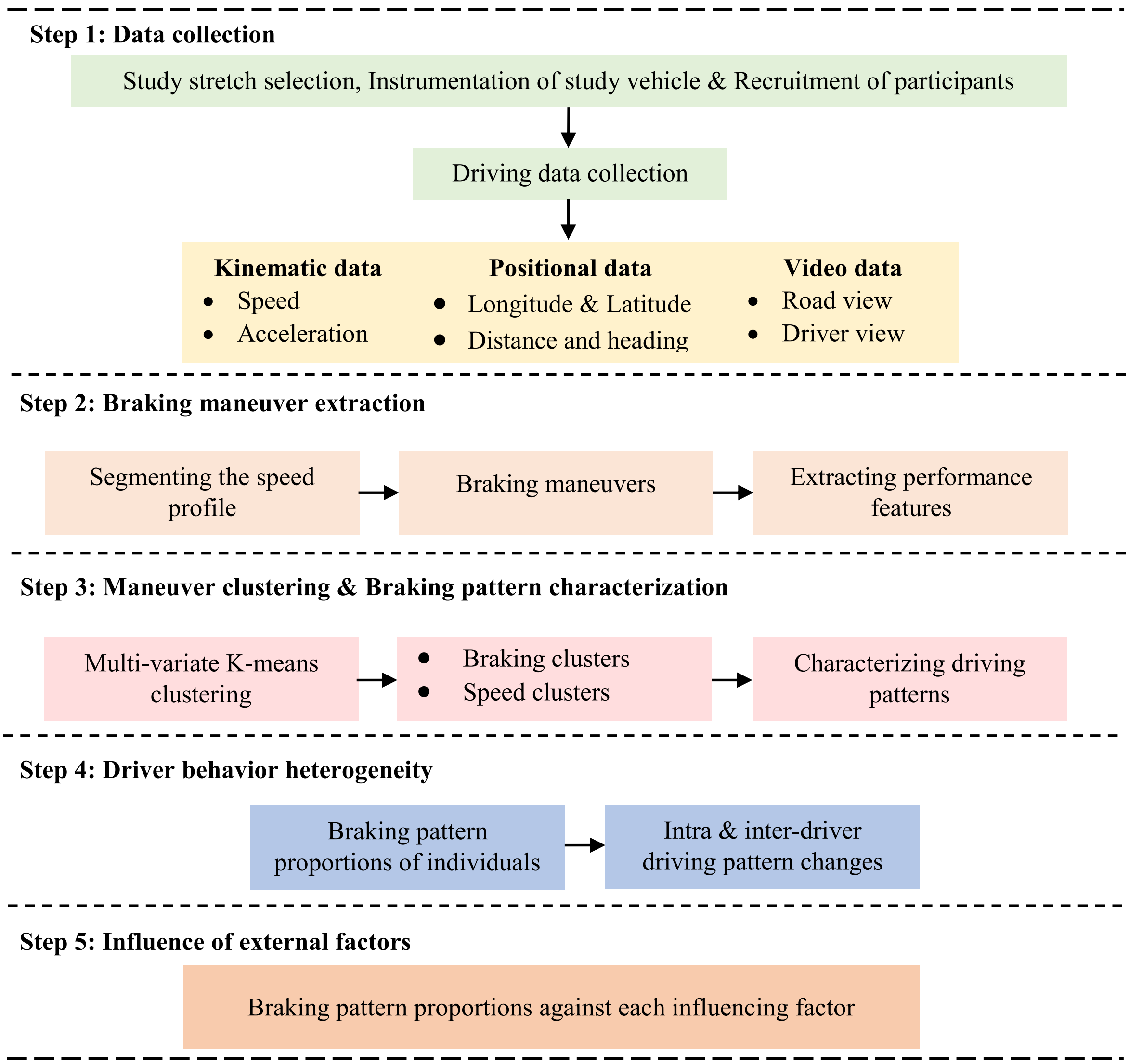

Figure 1: The framework of the study methodology

2.2 Data extraction

Braking event is a maneuver, where drivers decelerate or reduce the speed as a response to the surrounding traffic situation. The longitudinal decelerations resultant of brake applications are considered as braking events in this study. To understand the braking profiles of individuals, the braking events exhibited during the study period are extracted. The data extraction process is divided into two stages.

In the first stage, the braking maneuvers are extracted from the continuous speed profiles captured at a frequency of 10 Hz. The rate of change in the speed profile is used as a reference to segment the profile into acceleration and braking maneuvers. The segments with negative rate of change in speed are considered to represent the braking maneuvers. Further, the free-decelerations (< 0.5 g), congested events (<15 kmph speed), and low-deceleration braking maneuvers (<0.2g) are eliminated to remove the insignificant maneuvers. The final dataset consists of total 995 braking events corresponding to 15 drivers.

For the identified braking events, the respective driving performance features are extracted. The features include the maximum speed (V_{max}), minimum speed (V_{min}), mean speed (V_{mean}), standard deviation of speed (V_{sd}), maximum longitudinal deceleration (LA_{min}, represented as minimum longitudinal acceleration), average and standard deviation of deceleration (LA_{mean} , LA_{sd}) exhibited over the braking maneuver. The detailed process of event data extraction using speed profile is discussed in [11]. In the second stage, the details regarding the surrounding driving environment are extracted for each braking maneuver by video analysis. The road geometry (straight section/intersection/curve), traffic condition (car-following/free-flow/congested), type of lead/crossing vehicle to which the driver responds (Heavy motor vehicle –HMV/ passenger car/two-wheeler/auto-rickshaw), and the state of driver distraction (No/Yes) are extracted for each braking maneuver manually through video observation.

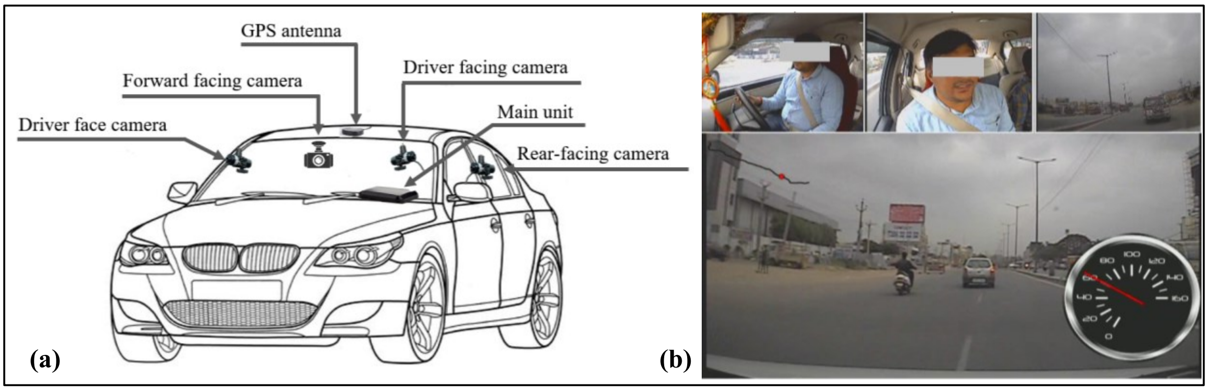

Figure 2: (a) Study vehicle and instrumentation; (b) Four camera views

3. Analysis and Results

3.1 Clustering

The multi-variate K-means clustering technique is used to identify various patterns of braking behaviour. The feature data is divided into two groups, one representing the nature of deceleration (LA_{min} , LA_{mean} , LA_{sd}), and another speaking of speed choices (V_{max} , V_{min} , V_{mean} , V_{sd}) exhibited over the braking maneuver. Given that each feature represents different aspects of driver behaviour, the feature data is scaled using Z-score standardization prior clustering. The clustering analysis is conducted separately on these two groups. The optimal k = 2 is chosen for both braking and speed feature data, based on the silhouette analysis. **Figure 3** shows the average positive silhouette values of all clusters, which indicates well-separation from the neighbouring clusters. Considering the optimal k-value of 2, the clustering analysis is performed on both the feature sets using k-means technique.

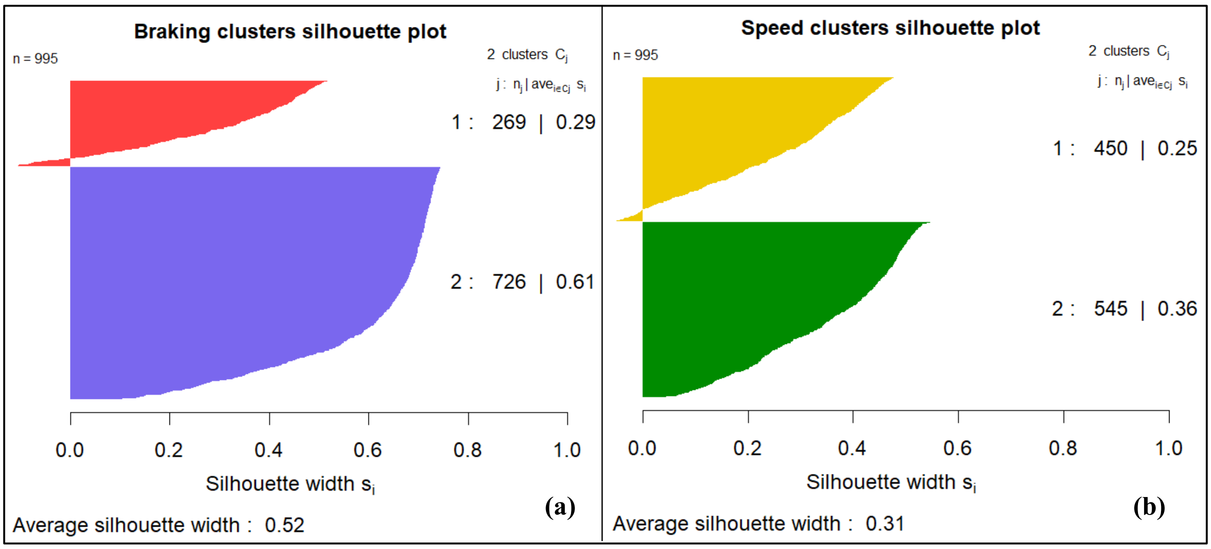

Figure 3: Silhouette values of (a) Braking clusters; (b) Speed clusters

The bi-plots of braking clusters are shown in **Figure 4 (a),** and speed clusters are shown in **Figure 4 (b)**. In case of braking clusters, the features are negatively correlated with the principal components, thus indicating that cluster-1 is ranging over higher values of deceleration, whereas cluster-2 is representing the lower deceleration values.

Similarly, in case of speed clusters, cluster-1 is representing higher speed values, and cluster-2 represents nominal/low-speed values. Based on the observation from bi-plots, and the respective cluster centroids (**Table 1**), the braking clusters are characterized to be representing aggressive and non-aggressive braking maneuvers. Similarly, the speed clusters are characterized as high-speed & nominal speed clusters. The cluster characterization is shown in **Table 1**.

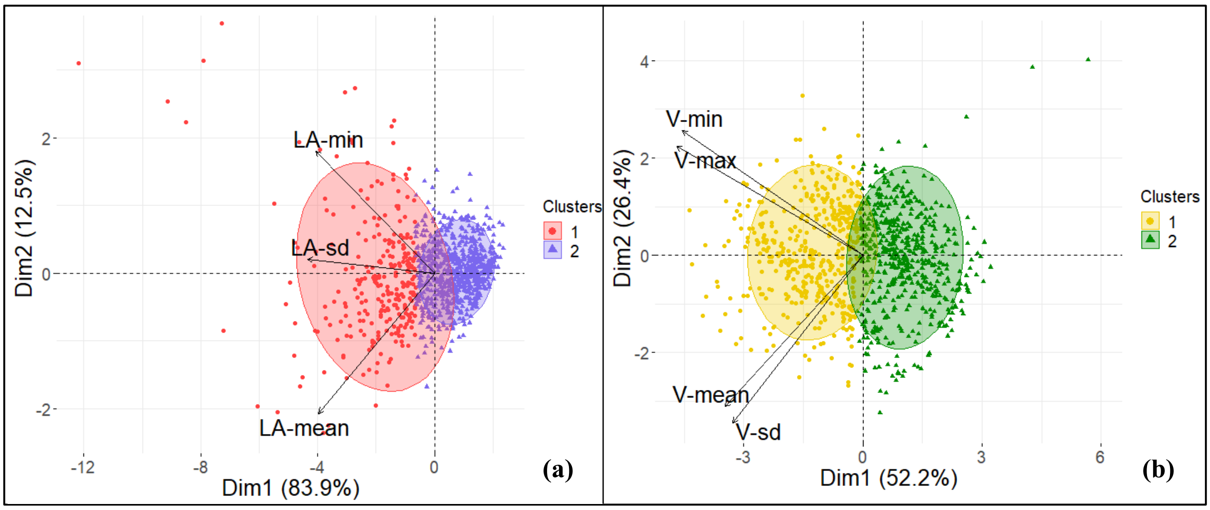

Figure 4: The bi-plots of (a) Braking clusters; (b) Speed clusters

Table 1. Cluster centroids and cluster characterization

Breaking feature centroids					
Braking Clusters		LA_{min}	LA_{mean}	LA_{sd}	*Classification*
1		0.38	0.14	0.09	Aggressive
2		0.25	0.09	0.06	Non-aggressive
Speed feature centroids					
Speed Clusters	V_{max}	V_{min}	V_{mean}	V_{sd}	*Classification*
1	65.78	44.59	54.24	14.28	High speed
2	40.83	18.88	31.34	16.29	Nominal

Each braking event is associated with a specific braking cluster, and a speed cluster. The combination of braking and speed clusters defines the driving pattern of that braking maneuver. Thus, for each event, the corresponding braking cluster and speed cluster are identified. Total four driving patterns are identified considering all the possible combinations of the braking and speed clusters. The driving patterns and the respective significance in road safety is shown in **Table 2**. Each pattern speaks a different behavioral aspect of the driver such as, pattern P1 representing the aggressive-high speed braking maneuvers, indicates the fatal or high-risky nature. The pattern P2 representing the aggressive-low speed maneuvers, indicates more rear-end collision tendencies. The pattern P3 speaks of non-aggressive braking maneuvers at high-speeds, which indicates good driving skills and driving stability. The pattern 4 indicates the non-aggressive braking exhibited at low-speeds, demonstrating the base-line braking behaviours.

Table 2. Braking pattern characterization

Patterns	**Braking**	**Speed**	**Significance**
P1	Aggressive	High	Fatal / high risky behavior
P2	Aggressive	Nominal	Rear-end collision tendencies
P3	Non-aggressive	High	Efficient driving skills
P4	Non-aggressive	Nominal	Base-line behavior

3.2 Driving Behavioral Heterogeneity

To understand the distribution of patterns with-in and across the drivers, the number of braking events falling under each pattern are computed for 15 drivers. The proportion of each pattern is determined by dividing the number of braking events in the respective pattern with the total number of braking events observed over the study period. **Figure 5** shows the proportion of driving patterns observed in each individual. It can be observed that, drivers are not exhibiting uniform braking behaviour and each driver is showcasing a minimum of three braking patterns with-in the drive period, indicating the intra-driver variability. Also, different drivers are exhibiting different proportions of driving patterns.

For example, driver D14 is exhibiting higher proportion (34%) of risky maneuvers, whereas drivers D11, D12, and D13 are predominantly showing (>70%) the base-line behaviour. Similarly, the efficient driving maneuvers can be majorly observed in drivers D1, D9 & D14, where 55 – 60% of the maneuvers are under pattern P3. The behavioural variation among the drivers might be due to the differences in driving habits and driving environment. Thus, the behavioral heterogeneity should be considered while assessing the driver, rather characterizing the entire drive period as safe or unsafe. The identified pattern proportions of individuals provide the detailed braking behavior profile of each driver, which in turn can be used to assist the individuals to improvise the way they usually drive.

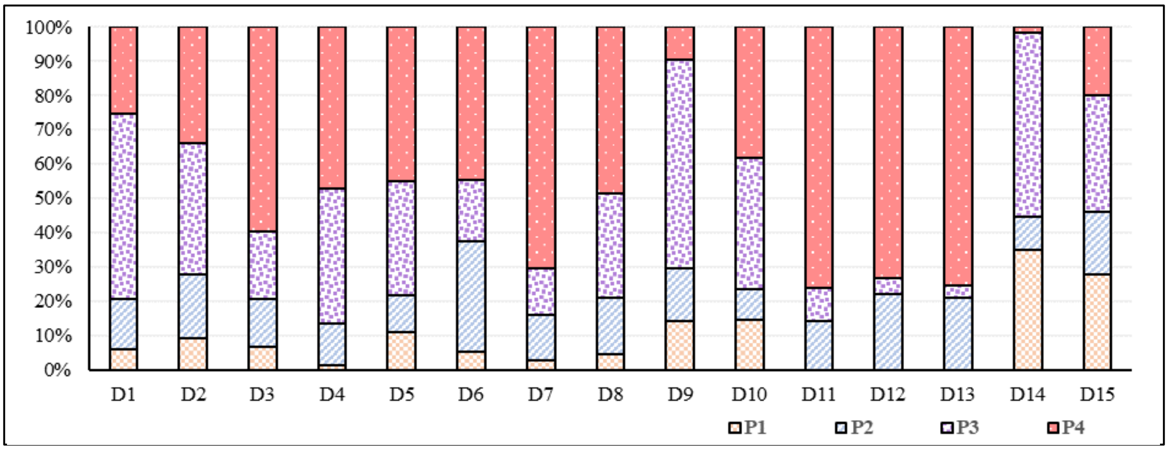

Figure 5: Proportions of driving patterns in individual drivers

3.3 Influence of External Factors

The identified patterns are observed against the levels of external factors. Total four factors are considered in this study: the road geometry, traffic condition, type of lead/crossing vehicle, and presence of driver distraction. For each driving pattern, the proportion of events under various levels of external factor are computed and shown in **Figure 6**. Also, the total proportions are computed, which indicates the dispersion of entire data against the levels of external factors. It should be noted that, the composition of events across the levels of external influencing factors is not uniform. Hence, comparing the proportion of events with-in a pattern across the factor levels is not meaningful. In other words, the proportion of events under different levels of road geometry (straight section/intersection/curve) with-in P1, or P2 can't be compared. Thus, the overall composition (total) of each factor is considered as a benchmark to examine the break-down of proportion of events in each pattern. The differences in the compositions of driving patterns provides insights about the influence of driving environment on driving patterns. The high risky behaviours (events under pattern P1) appears to be happening more over straight sections, under free-flow conditions. In case of car-following scenarios, the drivers are observed to be exhibiting risky braking responses while following HMV and two-wheelers, compared to the other vehicles. Also, the distracted drivers are executing more-risky braking maneuvers. The aggressive braking patterns associated with low speeds (pattern P2) appears to be predominant at intersections, and during congested traffic conditions. This supports the pattern characterization, as the rear-end collisions are more likely to happen during congested traffic situations, especially in Indian driving conditions.

Given that, the driving patterns are showing variation concerning the external driving environment, a model can be developed to predict the driving outcome under specific external conditions. The behavioural predictions based on real-time data would be highly useful to develop personalized driving assistance systems.

4. Discussion

This research explored the braking behavior of passenger car drivers using unsupervised methodology. The study resulted in total four braking patterns, each indicating different characteristic of the braking maneuver. The identified patterns are further associated with the respective external driving conditions to understand the influence of factors effecting braking behavior.

The commercial success of any transportation company is heavily linked to the quality of drivers. The consequences of poor driving behavior are very apparent and widely recognized. Road traffic accidents often occur due to driver (human) error and can be extremely costly to the firms as well as the government. Tracking drivers driving behavior can ensure the drivers remain constantly aware and are motivated by the improvements they are making. This study findings aids in formulating standards against driving which gently forces the drivers to drive safer. Making use of the study results, risk indices for drivers can be obtained, which helps in the identification of drivers with unsafe driving practices. These risk factors can be used to develop insurance schemes and safety improvement policies, where drivers will be cautious of decisions and movements. Drivers can be intimated regarding safety hazardous locations and dangerous maneuvers to avoid getting into crashes. A mobile based application can be developed which can be used by the individual driver or by transport and logistics firms to track the drivers driving behavior at microscopic level. Further, the good driving behavior can be incentivized, and the bad driving behavior can be penalized.

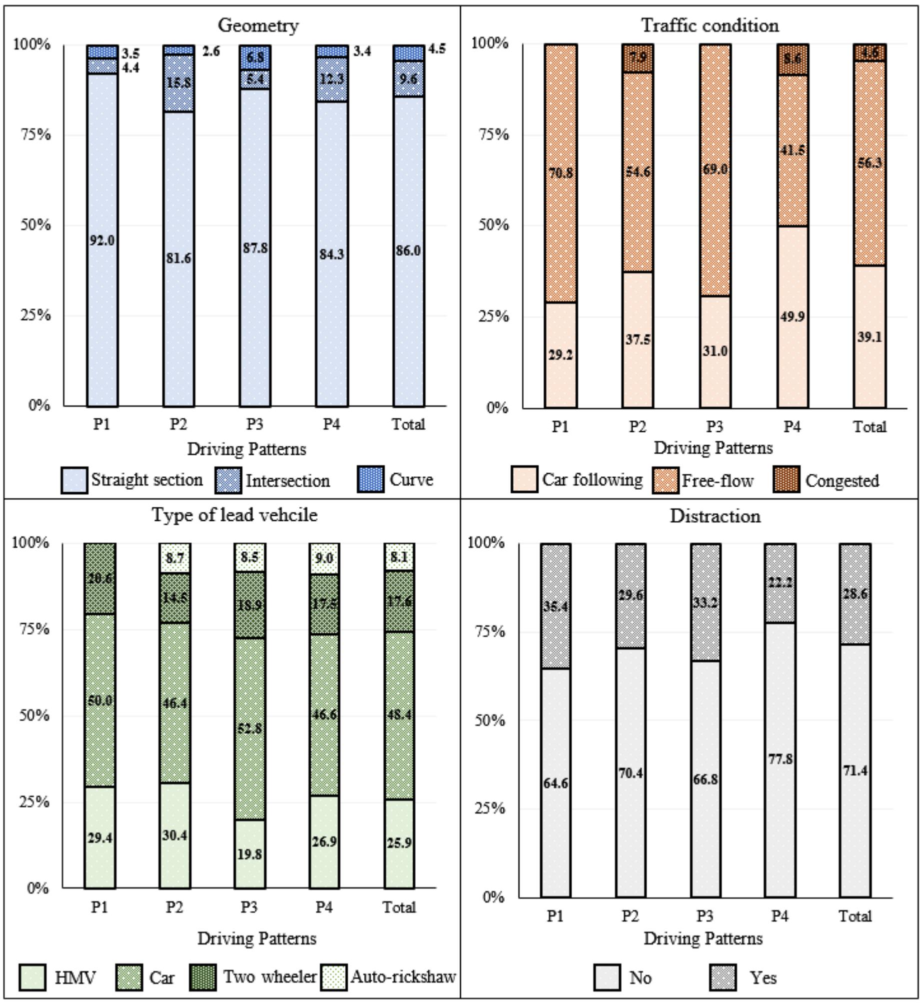

Figure 6: Proportions of events by road geometry, traffic condition, type of lead vehicle, and distraction among the driving patterns

5. Conclusions

In this paper, we proposed a methodology for assessing the driver behavior of individuals, specifically to identify different braking patterns exhibited in real-road driving conditions. The braking patterns were assessed by means of objective performance measures, using unsupervised techniques. Total four patterns of braking behavior were identified, indicating different aspects of braking behavior in the perspective of road safety. The study also presented the driver behavior variations at driver level, and against the levels of external influencing factors. The research outcomes have contribution towards road safety, as the identified at-fault braking behaviors may be further used to help drivers improvise the driving skills.

In the present study, the correlations between the identified patterns and the road safety is not objectively presented due to the unavailability of crash data. The relation between different driving paterns and the road-crash data would give deeper insights about the nature of patterns in the aspect of safety. Also, more number of drivers and the respective multi-trip driving data would help to assess the driving stability of individuals. The methodology can be extended to different maneuvers such as acceleration, and lane-change, to develop a comprehensive driving assistance functions.

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