Driver Behavior Analysis of Older Adults at Road Intersections Using Naturalistic Driving Data

by

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Abstract

In this study, I have understood driving behavior difference between drivers with Mild Cognitive Impairment (MCI) and drivers without Mild Cognitive Impairment (Non-MCI) and understood the relationship between cognitive abilities of different individuals and their driving behavior. I have developed different methodologies to extract different measures representing driving behavior at road intersections. Multiple driving individuals residing in MCI and Non-MCI were recruited and their driving data and physiological data were recorded. Driving behavior was represented in two domains (Physiological domain and Vehicular domain). First goal of this study was to find out driving behavior difference between MCI and Non-MCI group of drivers using both physiological domain measures as well as vehicular domain measures using statistical analysis. Second goal of this study was to find relationship between cognitive abilities and driving performance measures. To find out this difference braking patterns of drivers were analyzed just before the intersection to understand the effect of declined cognitive abilities on the effectiveness of driving. Based on the results of the experiments machine learning model was trained to classify drivers in two different classes based on their vehicular and physiological domain driving performance measures. From the experiments performed, I found out that there is some significant difference between MCI and Non-MCI group of drivers in both Physiological domain measures as well as Vehicle domain measures.

Chapter 1. Introduction

Traffic accident statistics have shown intersection crashes to be a major source of conflicts. 1.3 million intersection crashes were reported in 2015 which caused 16% of all fatal crashes and accounted for about 20% of all reported crashes [1]. Among the accidents happened at intersections, it was reported by National Highway Transportation Safety Administration that more than half of total involving the drivers with age greater than 65 [2]. According to another report by NHTSA showed a massive increase of 31% increase in older adults over 10 years of span from 2008 to 2017 [16]. These drivers cover 19% of overall licensed drivers in United States. As a consequence, it necessitates special attention to driving safety at intersections among older drivers.

In order to improve the driving performance and safety, it is critical to model and analyze drivers' behavior at intersections and the drivers' behavior model could be integrated into advanced driver assistance systems to provide personalized assistance to drivers at intersections. Modeling drivers' behavior at intersection aims to recognize normal operations and detect potentially dangerous operations. However, drivers' behaviors at intersection are inevitably dependent on the driving manners and the functional abilities, namely, the driving behaviors at intersection in the naturalistic driving conditions will vary with differences in individual factors. Therefore, it is necessary to take the individual factors into account when model the drivers' behavior at intersections.

The objective of this study was to investigate how cognitive abilities affect the drivers' behaviors at intersections and whether any specific domains of cognition could be significantly related to drivers' behaviors at intersections. To be specific, the driving behavior measurements including the driving performance and vehicle dynamic data were compared between subjects with different cognitive test scores. The correlation between cognitive scores and the driving behavior measurements were analyzed. Moving along this direction, in this work the subjects were assigned into two groups, i.e., Mild Cognitive Impairment (MCI) group and Non-Mild Cognitive Impairment (Non-MCI) group. MCI was defined as a cognitive state that lies between normal aging and dementia [3]. MCI patients' cognitive abilities are below the level which is expected to be normal but above the level of dementia.

Several research efforts have attempted to explore the association between driving behaviors and MCI. Wadley et al. [4] compared participants with MCI to control participants on a driving evaluation conducted by a driving rehabilitation specialist. The results demonstrated that MCI patients were significantly different from the control patients in global rating of driving performance as well as in features of left turns, lane control. However, no significant difference was found in right turns, gap judgment, steer steadiness and speed maintaining. Frittelli et al. [5] compared 3 driving features, i.e. the length of run, mean time to collision, and number of off-road events between subjects with mild Alzheimer's disease, subjects with MCI, and healthy controls. The results demonstrated that MCI subjects had only a significantly shorter time-to-collision than healthy controls while the used 3 driving performance did not significantly correlate with overall cognitive function. Kawano et al. [6] compared the driving performance of adults with MCI, older adults with normal cognition, and younger adults with normal cognition in 3 tasks, i.e. a road-tracking, a car-following, and a harsh-braking task. A significant difference between adults with MCI and older adults with normal cognition was observed only on the car-following task. Devlin et al. [7] reported that MCI patients performed more poorly than controls in a series of performance measurements, such as approach speed, number of brake applications on approach to the intersection, failure to comply with stop signs, and braking response times on approach to a light change. However, they also stated that the difference failed to reach statistical significance. Griffith et al. [8] suggested that there may be a link between hippocampal atrophy and higher risk for less-than-optimal lane control in subjects with amnestic MCI. Man-Song-Hing et al. [12] reviewed the work done during 1995 to 2005 and stated that drivers with MCI are poorer drivers than Non-MCI drivers. It was also concluded in their work that it was not clear about the MCI drivers meeting with accidents was much higher as compared to Non-MCI drivers. It should be noted that most of the previous research use the simulated driving environment or pre-determined driving route instead of naturalistic driving scenarios. However, the drivers' behavior in simulator and real conditions are not identical [9]. Wang et [13] determined the significant difference between MCI and Non-MCI group of drivers by studying their physiological patterns. Their study was related to driving in different scenarios such as Ramp, Freeway with heavy traffic, Freeway with low traffic, Local road with traffic, etc.

In this work, I focus on the modelling and understanding of the driving behavior at intersections. In the rest of this work, I first provide the information about the data used in the research followed by methodologies used to extract driving behavioral features. Next, I will provide the data collection information and data description used for this study. In section 4 I will explain the experimental setup used to conduct different experiments and also the results achieved by the experiments. After that I will discuss the results and potential opportunities of improvements.

Chapter 2. Data Description

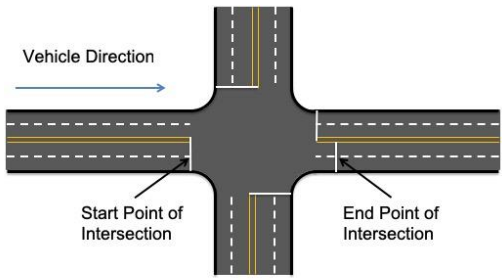
The data used in this study was recorded for a total of 37 drivers (14 MCI and 23 Non-MCI) aging between 65 and 88 years (74.97 $\pm$ 6.00 years). Out of all 37 participants 18 were male (75.74 $\pm$ 6.70 years) and 19 were female (73.57 $\pm$ 4.52 years) drivers. To ensure equal amount of distribution almost equal male and female drivers were recruited. Each driver was asked to drive for at least 5 days not necessarily consecutive days. Based on the participants availability appointments were made. Total driving time for each participant ranged from 1 hour 45 minutes to 8 hour 6 minutes. Average driving time for each participant was around 4 hour and 45 minutes. It should be noted that all the information mentioned above is using only the valid data. No data samples were moved to generate or manipulate the experimental results. All the individuals were licensed for at least 10 years.

To record the data a specific setup from Race technology was installed in every vehicle. This device recorded the time stamp information, speed, distance, steering angle, lateral acceleration, longitudinal acceleration, etc from the vehicle. Before using the raw data, it was important to determine the credibility of the data being recorded. A total of small set of signals were found that can be used for the study. For this reason, in this study from the vehicle data only 3 signals were used (Time stamp, Speed, Distance). Apart from the vehicle data individual drivers' physiological data were recorded using Bio harness and Shimmer devices. A total of 5 important signals were recorded (BR, HR, HRV, GSR, and ECG). In order to reduce complexity of the research only 4 signals were used to in the experiments (BR, HR, HRV, and GSR). It should be noted here that both Bio harness and Shimmer devices had different sampling rate to collect the physiological measures. Bio harness had a sampling rate of 1Hz, and Shimmer had sampling rate of 51.2Hz. Wang et al [13] has determined the frequency required to capture the important information form physiological signals. A final sampling frequency of 10Hz was used to determine the arousal level from the physiological signals. Bio harness data was up sampled, and Shimmer data was down sampled to have 10Hz of sampling frequency. Whenever required linear data interpolation was used to determine samples while both up sample and down sample process. Both the sensory devices had a linear range of operation due to which linear data interpolation was used to get the samples with missing time stamps. Individual drivers' vehicles were used to record the data.

Individuals were asked to take a test before their data was recorded and based on the test results the drivers were classified between MCI and Non-MCI groups by experts in the field. The tests included a simulation drive for 30 minutes and other tests related to determine cognitive abilities of each driving individual. 5 different age adjusted cognitive domain scores including Attention function, Working memory, Executive function, Processing speed and Premorbid functioning were generated by the experts in the field. Each participant was told to complete the test if any only if they feel comfortable to do so. Participants were also asked to fill out a questionnaire by the end of each day to collect additional information about their day while driving. Any of the results of this study are not based on the questionnaire reasoning. While recording the trips there were some scenarios where the data was not good. All of those trips were discarded for this study. All the participants' information was kept hidden for the safety of the participants. Figure 2 represents total amount of valid data for each participant.

Table 1. Analysis Data Information

Intersection Scenario	Total MCI Samples	Total Non-MCI Samples	Total Samples Used
Stop Right	147	274	421
Stop Left	128	167	295
Stop Straight	149	167	316
TL Red Right	70	194	264
TL Red Left	94	237	331
TL Red Straight	328	646	974
Stop	424	608	1032

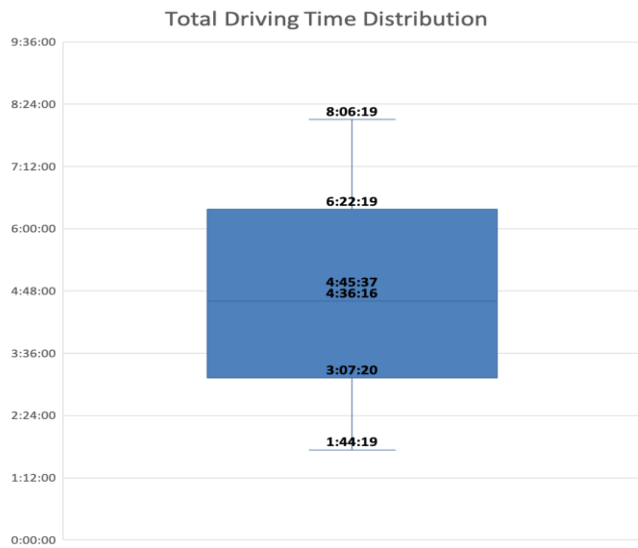


(a) Start point and end point guidelines used

(b) Start point example

(c) End point example

Figure 1. Intersection Labelling



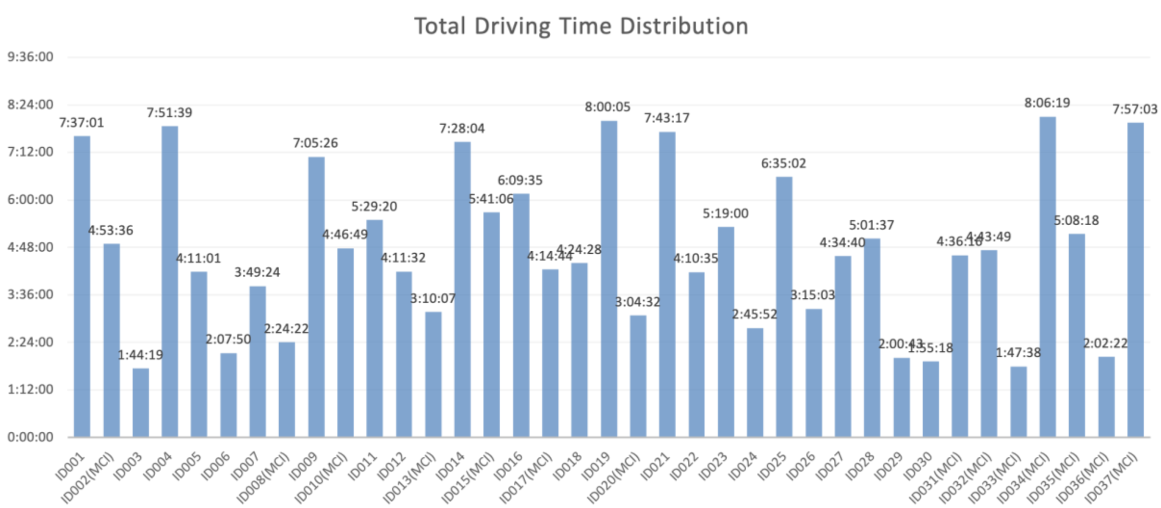
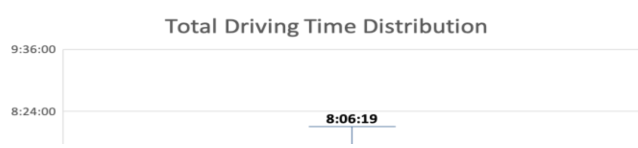


Figure 3. Data Distribution



Chapter 3. Methodologies

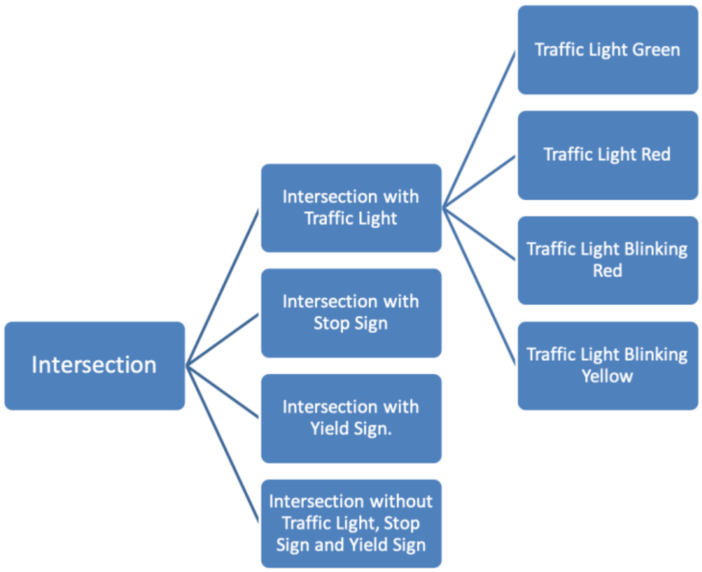
1. Task Description

Different types of intersections require different set of actions to cross the intersection. These actions depend on the drivers' destination and these actions can be influenced by design of the intersection and roads merging at that intersection. Due to this reason single drivers' behavior may be different in different intersection type. For that reason, we have classified the intersection scenarios in different classes. Figure. 3(a) illustrates different intersection types and Figure. 3(b) shows possible maneuvering actions at all different intersections. In this work, I have analyzed 2 of these different intersection types (Stop Sign and Traffic Light Red) shown in Figure. 3(a), Traffic Light Red and Stop Sign. These 2 intersection cases require drivers to perform several sets of complex tasks. These tasks include drivers' attention towards traffic signs or stop signs, apply brakes and find safe time to clear intersection. As these cases consists of complex tasks and also have similar necessary driving actions, I choose to study these cases. Intersection with yield sign also contains all the 3 maneuvering actions mentioned in Figure. 3(b). Since driving route for each driver wasn't fixed, only few occurrences were present for this type which may be biased and because of that reason intersection with yield sign was not analyzed in this study. For both the chosen intersection cases, driver must follow similar type of actions. First the driver needs to decide if he can go through the stop sign safely. Based on the number of vehicles present, the driver's decision may differ for the same intersection. If the driver decides he cannot go through the intersection he has to reduce the speed such that he can stop the vehicle comfortably, before the stopping line or at a safer distance from the vehicle in front. Different drivers may have different patterns of achieving a complete stop at intersection and that was modeled for this study.

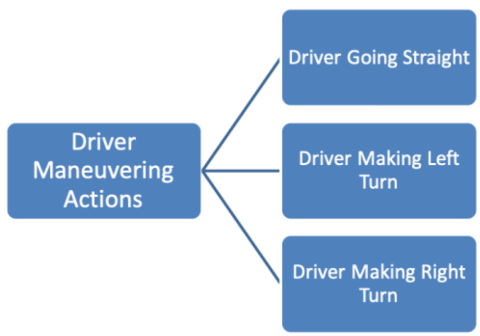
To extract the intersection segments in the recorded trips, manual labeling was done using recorded road view videos. To mark the intersection segments, different guidelines were followed at the time of labeling. Figure. 1 illustrates these guidelines used to mark start point and end point of intersection. By using these guidelines symmetric start and end points were identified for all the intersections. Since all the drivers needs to apply the brakes before the start point, data before start point of intersection was added along with the labelled intersection data and whenever required further data was added based on the speed data.

2. Driving Behavioral Analysis From Features

In this section, I present the methods in detail used to extract the driving behavioral features at intersections. To identify driving behavior at intersection, total of 22 features were extracted. These features were extracted in Vehicle Domain as well as Physiological Domain. These features included brake reaction time, brake time, decelerating time, brake distance, decelerating distance, maximum deceleration, average deceleration, maximum jerk, average jerk, maximum jerk, minimum speed, Breadth Rate (BR), Heart Rate (HR), Heart Rate Variation (HRV), Skin Conductance (GSR), et cetera. The naturalistic driving data was recorded by vehicles on board diagnostics system, which includes sampling time, vehicle's speed, traveling distance, etc. Using vehicle's maximum travelling speed before intersection and minimum traveling speed at intersection decelerating time and decelerating distance were calculated. To extract brake reaction time, brake time, brake distance features, longitudinal dynamics model was built, and then these two features were accurately extracted based on the vehicle dynamics model. Deceleration data was extracted using sampling time and the vehicle's speed. Jerk measure was extracted using vehicle speed, acceleration and sampling time. All the physiological measures were recorded using Bio Harness and Shimmer devices. All the participants were asked to wear these two devices to record their physiological signals.



(a) Intersection classification based on traffic signs



(b) Intersection classification based on traffic signs

Figure 5. Intersection Classification Guidelines.

3. Vehicle Domain Measures

3.1 Brake Reaction Time

Brake reaction time is an important factor that reflect driver's response performance at intersections. When the acceleration pedal and the brake pedal are not activated in the deceleration process, the longitudinal model can be expressed as:

$$\mathrm{ma}_0 = -mg\mu_1$$

Where, m is the vehicle's mass, g is the acceleration of the gravity, μ_1 refers to is the rolling friction coefficient, a_0 and refers to theoretical deceleration threshold. Theoretical deceleration threshold can be obtained as:

$$a_0 = -g\mu_1$$

Thus, the brake point can be detected using deceleration threshold. However, the real-world data may contain some noise, which may cause inaccurate brake point detection by using deceleration threshold. To address this problem, we have used a large amount of data to identify the maximum noise on the deceleration. If the maximum noise on the deceleration is defined as a_0, the deceleration threshold for detection the brake point can be depicted as:

$$a_{threshold} = a_0 + \Delta a_0$$

The total deceleration process at intersection is shown in Figure. 4. At timet_1, the driver saw the intersection (stop sign or red traffic light) and the driver release the acceleration pedal. At timet_2, the driver realized he can't go through the intersection and stepped on the brake pedal. At timet_3, the driver realized he/she should go through the intersection and released the brake pedal. In the deceleration process, the brake reaction time can be defined as time between driver saw the intersection and the time at which driver stepped on the brake pedal, namely from t_1 to t_2. The brake reaction time is an important factor that reflect driver's behavior while using brake pedal. According to (1)-(3), we know the deceleration thresholds to detect the time t_1 and t_2 can be depicted as:

$$a(t_2) = a_{threshold}$$

Thus, the brake reaction time can be easily calculated by:

$$t_{reaction} = t_2 - t_1$$

3.2 Brake Time

Brake time is an important measure in understanding the driver's behavior in applying the brakes to make stop at intersections. Based on the vehicle dynamics model mentioned above when the driver starts to apply the brakes acceleration goes below$a_{threshold}$, this point is used as starting point to determine the brake time. According to Figure. 4, we know the acceleration with go below $a_{threshold}$ just after timet_2. Thus t_2 can be used as starting point of brake time. Once the driver feels safe, he/she take the leg from the brake pedal to start accelerating the vehicle. When driver takes his/her leg from the brake pedal due to minimum initial torque of the vehicle, it starts to accelerate. As we know after this point the acceleration will increase and driver has stopped applying the brakes, thus this time can be used as ending time of brake time and is shown as t_3 in Figure. 4. Total brake time can be calculated as:

$$t_{brake} = t_3 - t_2$$

3.3 Decelerating Time

Brake time and Brake reaction time are two measures individual events. These features may get overlapped between other drivers due to speed and different decelerating patterns. Decelerating time is also one of the important time domain measures that can represent the driving behavior of any individual at intersections. All the time domain features were extracted in seconds to represent each intersection sample with high accuracy. Time was extracted from time stamp data from OBD data.

3.4 Brake Distance

Brake distance is another factor that reflect driver's behavior at intersection. Brake distance can be defined as total distance travelled by vehicle during brake time. The brake distance can be calculated as:

$$\mathrm{d_{brake}} = \int \mathrm{vdt}$$

3.5 Decelerating Distance

Decelerating distance can be identified as distance taken by driver to reduce speed of vehicle. This measure provides information about distance taken by each driver in order to reduce the speed of vehicle at intersection to achieve minimum travelling speed at intersection. To extract this measure distance data from OBD data was used and can be calculated as,

$$\mathrm{D} = \mathrm{D_{mins}} - D_{maxs}$$

Here, $\mathrm{D_{mins}}$ is travelled distance at minimum speed near intersection and $\mathrm{D_{maxs}}$ is travelled distance at maximum speed before intersection and D represents total distance used to reduce speed. As decelerating distances and brake distances cannot be in kilometers, both measures were converted to meters from kilometers.

3.6 Deceleration Rate

Deceleration rate is a critical factor to reflect driving stability and comfort. The research in [11] indicates when the deceleration rate is greater than 0.9, passengers will feel uncomfortable. The deceleration rate can be calculated as:

$$a(t_k) = -\frac{(v(t_k) - v(t_{k-1}))}{(t_k - t_{k-1})}$$

To analyze driving behavior in driving stability and comfort, the maximum deceleration rate at intersections can be calculated. Assuming the deceleration rate at an intersection can be expressed as:

$$A = [a(t_1), a(t_2), \dots, a(t_n)]$$

The minimum deceleration rate and the maximum deceleration rates can be depicted as:

$$a_{min} = \min(A), a_{max} = \max(A)$$

Maximum deceleration rate was used as a measure which is represented as a_{max}. It was believed that for every driver maximum deceleration rate should be a unique quantity since this measure represents comfort level of driver. In order to extract more information from the deceleration rate data average deceleration was calculated during brake time period and used as an additional measure. As the mild cognitive impaired drivers tend to respond slowly maximum deceleration rate should represent important information directly related to cognitive impairment of the drivers.

3.7 Jerk Rate

Jerk rate was defined as second order derivative of velocity over time or first order derivative over time. Jerk represents the rate of increase or decrease of acceleration or deceleration. Jerk directly represents the comfort/discomfort level of driver in the vehicle. As mentioned above different driving individuals usually have different comfort levels while driving in vehicle this measure can represent the important driving pattern such as maximum jerk represents highest of rate of change in acceleration related to accelerating force applied, minimum jerk represents the highest rate of change in deceleration related to brake force applied. Apart from these two measures average jerk was also calculated by averaging the overall jerk. Average jerk represents the comfort level distribution of the driver while accelerating and decelerating combined. As deceleration rates were used in this experiment the equation is negated such that positive jerk rate represents rate of change of acceleration and minimum jerk represents rate of change of deceleration. Jerk rate can be calculated as:

$$J(t_k) = \frac{-\left(a(t_k) - a(t_{k-1})\right)}{(t_k - t_{k-1})}$$

3.8 Minimum Speed

It was observed that not all the drivers make a complete stop at a stop sign and at intersections with traffic light red and driver making right turn without no turn on red sign present. This measure represents critical driving behavior at intersection. As we know that not all the drivers make complete stop at stop signs, and in case of mild cognitive impaired drivers it is much critical to make a complete stop due to higher amount of response time. This measure is one of the most important measures which represent the driving style of driving individual. It was believed that this measure will represent the driving behavior of drivers with mild cognitive impairment, since they tend to respond slowly.

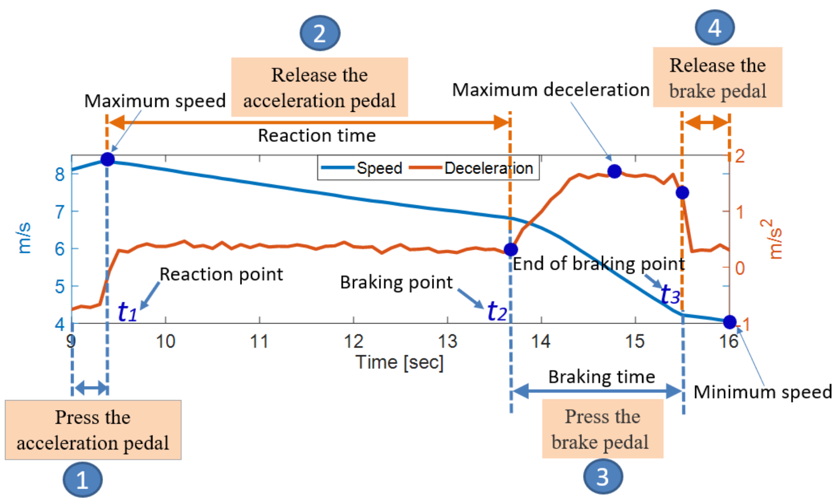


Figure 7. Visualization of Feature Extraction Methodologies

3.9 Normalization of Vehicle Domain Measures

Since, most of these features are highly dependent on vehicle speed and acceleration the features need to be normalized. There was no clear way since time domain features were dependent on speed. So, the data can be normalized in speed domain. The issue with normalizing the features based on min and max speed cannot be performed due to different speed limits on different road conditions. Each segment of the data can be normalized to a consistent value using GPS data and speed limit information for each segment of the road. Since this process is computationally extensive this method was not used in this study. Instead we normalized the features in another domain. Brake time and Brake reaction time measures were normalized using the following equation:

$$t_{reaction_{norm}}=\frac{t_{reaction}}{t_{reaction}+t_{brake}}, t_{brake_{norm}} = \frac{t_{brake}}{t_{reaction}+t_{brake}}$$

Similarly, distance domain measures were also normalized and used as a measure in this study. Normalized distance domain measures were calculated as:

$$d_{reaction_{norm}}=\frac{d_{reaction}}{d_{reaction}+d_{brake}}, d_{brake_{norm}} = \frac{d_{brake}}{d_{reaction}+d_{brake}}$$

Normalization provided the information in percentage domain which is a linear range and speed and time relativity was nullified. It was not proved so far about the effect of time, distance and speed domain information cannot be used directly. I believed that drivers may take similar route to travel from one place to another. Due to this reason time and distance domain features were not thrown away. These features were still used in the experiments performed.

4. Physiological Domain Measures

Wang et al. [13] developed a methodology to calculate the arousal level using 4 physiological signals. They determined the relationship between arousal level and physiological signals. 2 physiological signals (BR, HR) were found positively correlated with arousal level and 2 signals were found to be negatively correlated with arousal level (HRV, GSR). It was recommended in their paper to use at least 30 seconds of data because of statistical measures used to calculate final arousal level for 30 second span. Arousal level was calculated over brake time measure to capture any significant physiological changes while driver applies the brakes at intersection. Arousal level can be determined as:

$$Signal_{bt} = \mu[mean(Signal), median(Signal), Q1(Signal), Q3(Signal)]$$

$$Arousal_{bt} = \mu[|BR_{bt}|, |HR_{bt}|, |HRV_{bt}|, |GSR_{bt}|$$

Here, $Signal_{bt}$ represents single measure value evaluated based on 1 physiological signal. For all physiological signals $Signal_{bt}$ was evaluated. Since BR and HR signals were found positively correlated with arousal level these signals were normalized between 0 to 1 based on min and max values respectively. As, HRV and GSR were negatively correlated with arousal level these signals were normalized between 1 to 0 based on min and max values respectively. In$Signal_{bt}$, bt represents samples during brake time measure.

To determine the relationship with physiological signals and driving performance average of individual signals were used at intersection as well.

$$BR_{bt} = \mu\left(BR_{t_1}, \dots, BR_{t_3}\right),\ HR_{bt} = \mu\left(HR_{t_1}, \dots, HR_{t_3}\right)$$
$$HRV_{bt} = \mu\left(HRV_{t_1}, \dots, HRV_{t_3}\right),GSR_{bt} = \mu(GSR_{t_1}, \dots, GSR_{t_3})$$

Apart from this since the brake time span was not always 30 seconds or above average of all the signals was taken as arousal level measure as well. This measure was identified as Average Arousal Level.

$$AvgArousal_{bt} = \mu(BR_{bt}, HR_{bt}, HRV_{bt}, GSR_{bt})$$

A total of 6 measures were extracted during brake time measure representing physiological response of each driving individual includingBR_{bt}, HR_{bt}, HRV_{bt}, GSR_{bt}, $Arousal_{bt}$, $AvgArousal_{bt}$.

Chapter 4. Experimental Setup and Results

All, the drivers the goal of this research was to understand the driving behaviour different between MCI and Non-MCI group of drivers and to find out relationship between cognitive abilities and driving performance measures. To understand the driving behaviour difference between drivers with MCI and drivers without MCI, a total of 3 experiments were conducted and based on the results of these experiments classifier was built that can identify drivers class based on current driving performance. The experiments as follows: a) Correlation Analysis, b) T-test Analysis c) Stopping Compliance Analysis. After completing all these experiments, I have built an SVM classifier to classify MCI drivers with Non-MCI drivers. I have also included results of SVM classifier experiments in this section. Next, I will explain the details about how the experiments were conducted. At the end of explanation for each experiment results are presented.

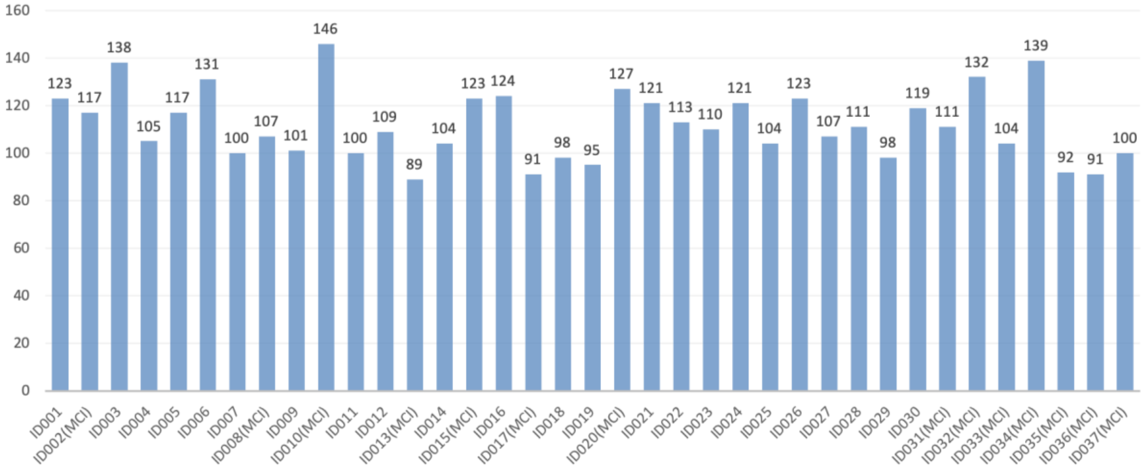
1. Correlation Analysis

One of the major goals of this research was to understand the relationship between cognitive abilities and driving performance measures for MCI and Non-MCI group of drivers. Since not all the drivers residing in MCI group showed declination in all the cognitive abilities it was important to find relationship between cognitive abilities and drivers driving performance measures. Different researchers have used simulator data to understand the relationship between the driving performance and relative cognitive abilities. But it was found that driver's behaviour in simulator and real world were found totally different from each other by [9].

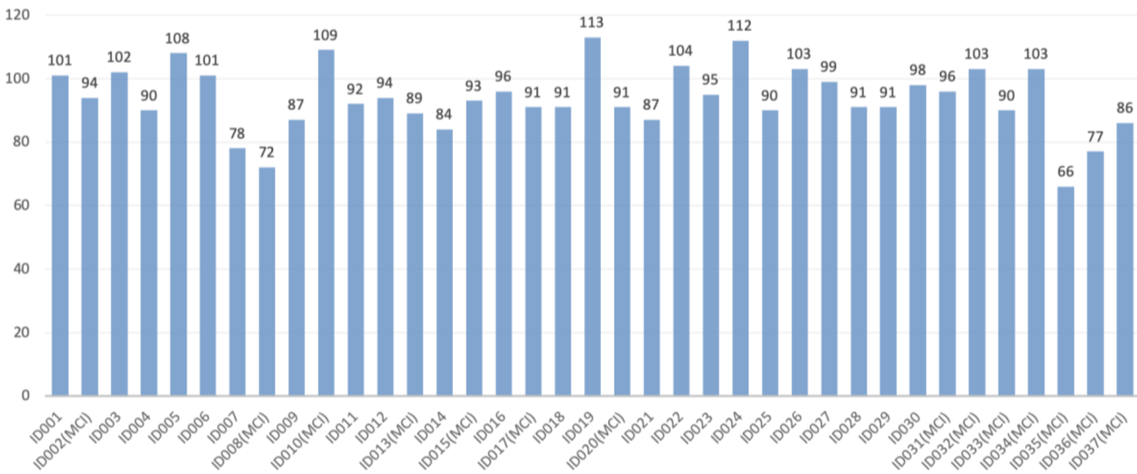
Individual participants were asked to take a test before starting to record their data to determine their cognitive abilities. The tests taken by participants were designed after rigorous research in the neuropsychological and cognitive abilities domain. According to article published by NCBI [15] total of 6 cognitive domain functions were found significant to determine the cognitive abilities in humans. These cognitive domain functions are Language and Communication, Learning and Memory, Attention and Vigilance, Processing Speed and Executive functioning.

Licensed personnel evaluated the scores for all the drivers and determined their age adjusted scores for all the 5 cognitive domain functions. All the scores for everyone are represented in Figure 5(a-g) Here is a list of cognitive functions used in this experiment,

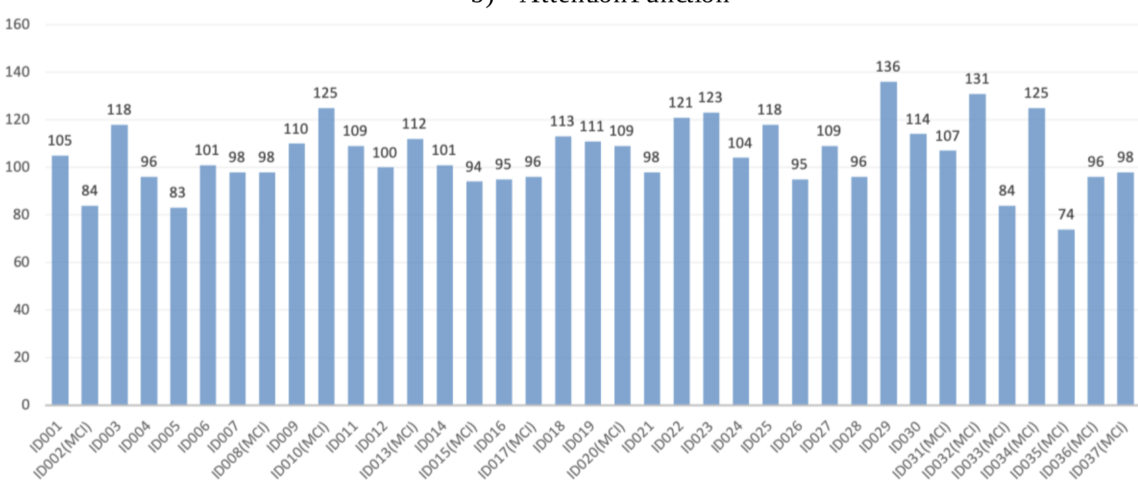
1. Executive Function (EF)
2. Attention Function (AF)
3. Working Memory Function (WMF)
4. Processing Speed Functioning (PSF)
5. Premorbid Functioning
    a. Reading Recognition (ORR PF)
    b. Picture Vocabulary (PV PF)
6. Memory Function (MF)



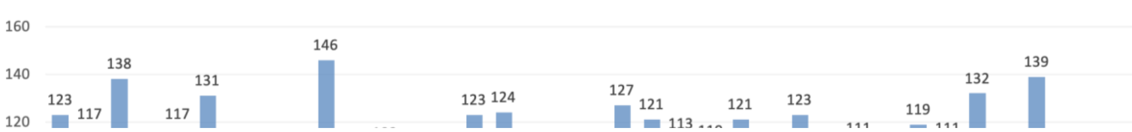
a) Executive Function

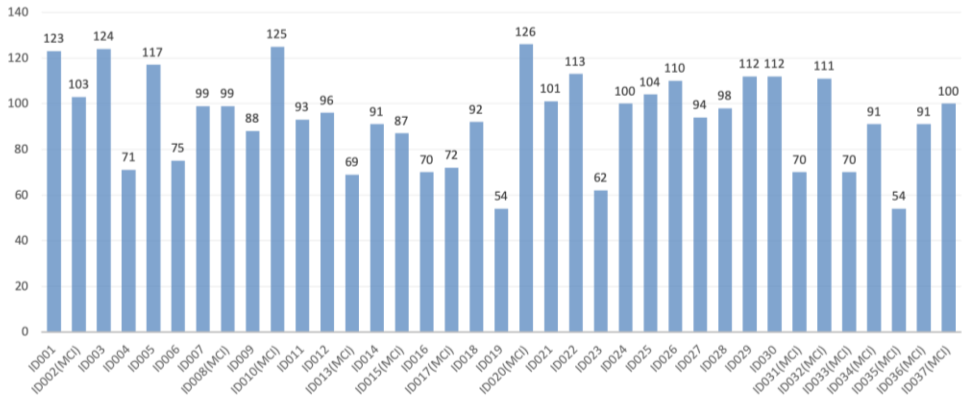


b) Attention Function

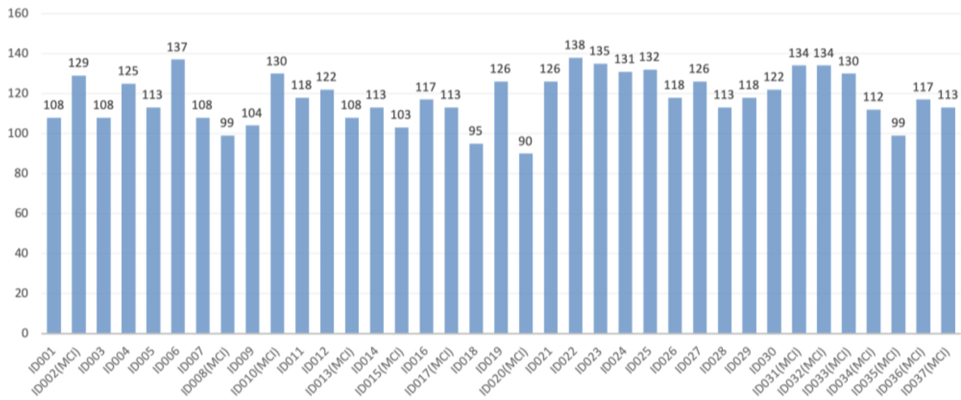


c) Working Memory Function

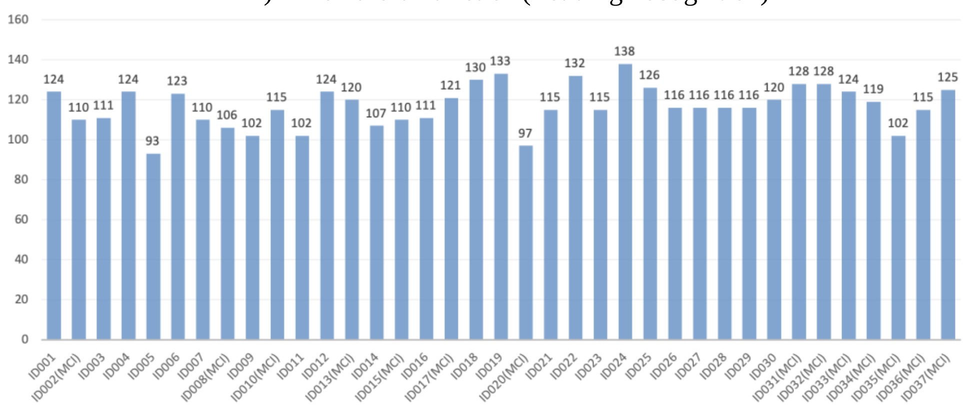




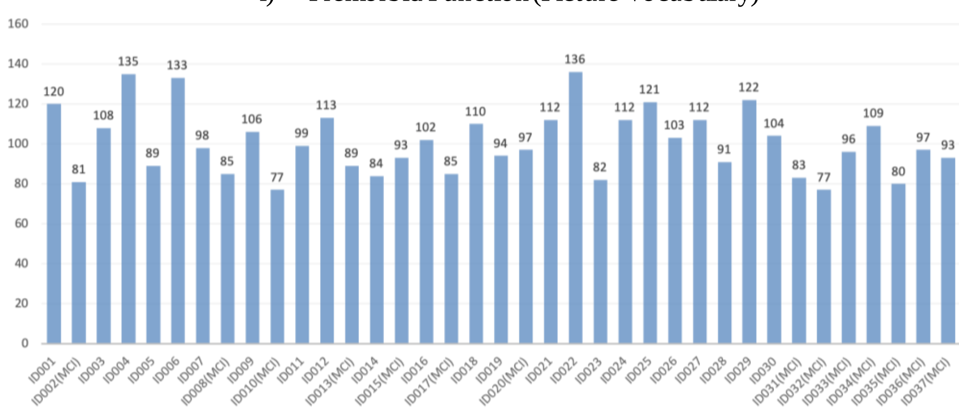
g) Processing Speed Function



h) Premorbid Function (Reading Recognition)



i) Premorbid Function (Picture Vocabulary)



j) Memory Function

Figure 9. Cognitive Score Distribution

As different roads have different speed limits not all the measures can be directly used. Speed, Time and Distance are relative quantities average of all these measures tend to be biased towards higher quantity values. To mitigate relative effect of all these measures, only normalized measures were used in this experiment. As one driver had multiple occurrences average over all the samples was taken as a single measure value to represent individual's overall driving behaviour in correlation analysis. There were certain criteria used to clean the data for analysis such as if a participant has only 1 sample for any intersection scenario his/her data was not used in correlation analysis. Using the methodology mentioned above for each driving individual only 1 measure value was derived. Each measure was used in correlation with all 7 cognitive scores. A total of 7 intersection scenarios were used in this experiment.

1. Stop sign with driver wants to go right (Stop Right)
2. Stop sign with driver wants to go left (Stop Left)
3. Stop sign with driver wants to go straight (Stop Straight)
4. Traffic light red with driver wants to go right (TL Red Right)
5. Traffic light red with driver wants to go left (TL Red Left)
6. Traffic light red with driver wants to go straight (TL Red Straight)
7. Stop sign (Stop)

Here, stop sign data consists of all the samples without classifying them based on driver maneuvering action. Data at stop signs can be used together since most of the stop sign intersection cases were found to have only 1 lane and driver is not required to change the lane as compared to traffic light red cases. In traffic light red cases the driver may need to maneuver to make right turn, left turn. Since driver need to maneuver the vehicle with these cases maneuvering action may affect the driving performance. Due to this reason traffic light red cases were not combined and analysed. One thing to note here is that there were no outlier removal methods implied on the data. All the possible samples were used in this experiment. Table 2 shows the total number of samples were used in this experiment and total number of drivers included in this experiment after applying the criteria mentioned above.

Table 2. Correlation Analysis Data Information

Intersection Scenario	Total Samples Used	Number of Drivers Data used
Stop Right	421	37
Stop Left	288	32
Stop Straight	301	26
TL Red Right	259	33
TL Red Left	330	34
TL Red Straight	972	36
Stop	1032	37

There are multiple measures used as driving performance measure in this experiment. A total of 15 measures were used in this experiment inclusive of both vehicle domain measures and physiological domain measures. These measures as follows:

- Vehicle Domain Measures:
  - Brake Reaction Time Percentage (BRTP)
  - Brake Time Percentage (BTP)
  - Brake Reaction Distance Percentage (BRDP)
  - Brake Distance Percentage (BDP)
  - Maximum Deceleration (Max Decel)
  - Average Deceleration (Avg Decel)
  - Minimum Jerk (Min Jerk)
  - Average Jerk (Avg Jerk)
  - Maximum Jerk (Max Jerk)
  - Minimum Speed (Min Speed)
- Physiological Domain Measures:
  - Average BR during Brake Time (Avg BR)
  - Average HR during Brake Time (Avg HR)
  - Average HRV during Brake Time (Avg HRV)
  - Average GSR during Brake Time (Avg GSR)
  - Arousal Level during Brake Time (Arousal)
  - Average Arousal Level during Brake Time (Avg Arousal)

Since correlation coefficient represents value ranging from -1 to +1 and there are no certain thresholds which can be used to determine significant correlation probability value was used to determine significant correlation. Probability of 0.05 or less was used as threshold to determine significant correlation between each measure and cognitive functions. Tables 3 to 9 contain the results of this experiment:

Table 3. Stop Right Correlation Analysis Results

	Cognitive Domain Measures						
Measure	**EF**	**AF**	**WMF**	**ORR PF**	**PSF**	**MF**	**PV PF**
Vehicle Domain Measures							
BRTP	0.07 (p = 0.69)	0.12 (p = 0.46)	-0.04 (p = 0.83)	0.30 (p = 0.07)	0.10 (p = 0.57)	0.00 (p = 0.98)	0.01 (p = 0.97)
BTP	-0.07 (p = 0.69)	-0.12 (p = 0.46)	0.04 (p = 0.83)	-0.30 (p = 0.07)	-0.10 (p = 0.57)	0.00 (p = 0.98)	-0.01 (p = 0.97)
BRDP	0.02 (p = 0.90)	0.11 (p = 0.46)	0.02 (p = 0.93)	0.26 (p = 0.11)	0.13 (p = 0.46)	0.04 (p = 0.82)	0.00 (p = 0.99)
BDP	-0.02 (p = 0.90)	-0.11 (p = 0.46)	-0.02 (p = 0.93)	-0.26 (p = 0.11)	-0.13 (p = 0.46)	-0.04 (p = 0.82)	0.00 (p = 0.99)
Max Decel	-0.19 (p = 0.26)	0.03 (p = 0.86)	-0.20 (p = 0.24)	-0.09 (p = 0.61)	0.06 (p = 0.73)	0.06 (p = 0.73)	-0.14 (p = 0.41)
Avg Decel	-0.19 (p = 0.27)	0.00 (p = 0.98)	-0.09 (p = 0.60)	-0.17 (p = 0.30)	0.02 (p = 0.93)	0.07 (p = 0.69)	-0.11 (p = 0.54)
Min Jerk	0.15 (p = 0.37)	0.23 (p = 0.17)	0.03 (p = 0.88)	-0.27 (p = 0.11)	-0.04 (p = 0.80)	0.02 (p = 0.92)	0.19 (p = 0.27)
Avg Jerk	-0.07 (p = 0.69)	-0.05 (p = 0.75)	0.00 (p = 0.98)	0.21 (p = 0.22)	0.14 (p = 0.42)	0.07 (p = 0.67)	-0.06 (p = 0.73)
Max Jerk	0.05 (p = 0.77)	0.12 (p = 0.48)	-0.15 (p = 0.38)	0.15 (p = 0.38)	0.00 (p = 0.98)	0.08 (p = 0.64)	0.02 (p = 0.90)
Min Speed	0.20 (p = 0.24)	0.29 (p = 0.08)	-0.16 (p = 0.35)	0.18 (p = 0.29)	0.14 (p = 0.41)	-0.02 (p = 0.90)	0.17 (p = 0.33)
Physiological Domain Measures							
Avg BR	0.17 (p = 0.31)	0.13 (p = 0.46)	0.18 (p = 0.28)	-0.19 (p = 0.26)	**0.43 (p = 0.01)**	-0.01 (p = 0.98)	-0.01 (p = 0.98)
Avg HR	-0.02 (p = 0.90)	0.24 (p = 0.16)	**0.36 (p = 0.03)**	0.04 (p = 0.80)	-0.13 (p = 0.46)	0.15 (p = 0.39)	0.15 (p = 0.39)
Avg HRV	-0.12 (p = 0.48)	0.04 (p = 0.82)	0.16 (p = 0.33)	0.29 (p = 0.08)	-0.18 (p = 0.28)	0.24 (p = 0.16)	0.24 (p = 0.16)
Avg GSR	0.03 (p = 0.87)	0.16 (p = 0.86)	0.26 (p = 0.11)	0.23 (p = 0.17)	-0.19 (p = 0.27)	-0.02 (p = 0.92)	-0.02 (p = 0.92)
Arousal	0.00 (p = 0.99)	0.16 (p = 0.36)	**0.40 (p = 0.01)**	0.23 (p = 0.18)	-0.14 (p = 0.42)	0.14 (p = 0.40)	0.14 (p = 0.40)
Avg Arousal	0.00 (p = 0.99)	-0.07 (p = 0.36)	**0.40 (p = 0.01)**	0.23 (p = 0.18)	-0.14 (p = 0.42)	0.14 (p = 0.40)	0.14 (p = 0.40)

Table 4. Stop Left Correlation Analysis Results

	Cognitive Domain Measures						
Measure	**EF**	**AF**	**WMF**	**ORR PF**	**PSF**	**MF**	**PV PF**
Vehicle Domain Measures							
BRTP	0.04 (p = 0.83)	-0.05 (p = 0.80)	-0.07 (p = 0.70)	0.19 (p = 0.29)	0.04 (p = 0.82)	0.18 (p = 0.33)	0.04 (p = 0.83)
BTP	-0.04 (p = 0.83)	0.05 (p = 0.80)	0.07 (p = 0.70)	-0.19 (p = 0.29)	-0.04 (p = 0.82)	-0.18 (p = 0.33)	-0.04 (p = 0.83)
BRDP	-0.02 (p = 0.93)	-0.11 (p = 0.55)	-0.01 (p = 0.94)	0.11 (p = 0.54)	0.00 (p = 1.00)	0.19 (p = 0.30)	0.02 (p = 0.92)
BDP	0.02 (p = 0.93)	0.11 (p = 0.55)	0.01 (p = 0.94)	-0.11 (p = 0.54)	0.00 (p = 1.00)	-0.19 (p = 0.30)	-0.02 (p = 0.92)
Max Decel	**-0.35 (p = 0.05)**	-0.03 (p = 0.89)	-0.32 (p = 0.08)	0.06 (p = 0.75)	-0.30 (p = 0.09)	0.09 (p = 0.61)	-0.01 (p = 0.94)
Avg Decel	-0.23 (p = 0.20)	0.08 (p = 0.65)	-0.28 (p = 0.11)	0.05 (p = 0.79)	-0.10 (p = 0.60)	0.15 (p = 0.40)	-0.07 (p = 0.72)
Min Jerk	-0.23 (p = 0.20)	-0.23 (p = 0.20)	-0.28 (p = 0.12)	-0.18 (p = 0.32)	-0.11 (p = 0.54)	0.04 (p = 0.84)	-0.13 (p = 0.48)
Avg Jerk	-0.21 (p = 0.24)	-0.34 (p = 0.06)	**-0.49 (p = 0.00)**	-0.25 (p = 0.17)	-0.26 (p = 0.15)	-0.24 (p = 0.19)	-0.34 (p = 0.06)
Max Jerk	-0.31 (p = 0.08)	-0.11 (p = 0.56)	-0.25 (p = 0.17)	0.07 (p = 0.71)	-0.28 (p = 0.13)	-0.03 (p = 0.87)	0.13 (p = 0.48)
Min Speed	-0.10 (p = 0.58)	-0.30 (p = 0.09)	-0.17 (p = 0.35)	-0.15 (p = 0.41)	-0.03 (p = 0.86)	-0.29 (p = 0.11)	-0.10 (p = 0.57)
Physiological Domain Measures							
Avg BR	-0.27 (p = 0.14)	0.08 (p = 0.65)	0.04 (p = 0.28)	-0.17 (p = 0.36)	**0.51 (p = 0.00)**	0.16 (p = 0.39)	-0.22 (p = 0.22)
Avg HR	0.08 (p = 0.66)	0.20 (p = 0.28)	0.31 (p = 0.08)	-0.01 (p = 0.98)	-0.18 (p = 0.33)	0.08 (p = 0.66)	0.15 (p = 0.41)
Avg HRV	-0.07 (p = 0.68)	0.00 (p = 0.99)	0.14 (p = 0.45)	0.27 (p = 0.13)	-0.17 (p = 0.34)	0.22 (p = 0.23)	**0.62 (p = 0.00)**
Avg GSR	0.04 (p = 0.83)	0.10 (p = 0.60)	0.16 (p = 0.38)	0.29 (p = 0.10)	-0.13 (p = 0.47)	0.15 (p = 0.42)	0.19 (p = 0.29)
Arousal	0.03 (p = 0.87)	0.04 (p = 0.84)	0.27 (p = 0.11)	0.25 (p = 0.17)	-0.09 (p = 0.61)	0.17 (p = 0.34)	**0.37 (p = 0.04)**
Avg Arousal	0.03 (p = 0.88)	-0.04 (p = 0.84)	0.27 (p = 0.11)	0.25 (p = 0.17)	-0.09 (p = 0.61)	0.17 (p = 0.35)	**0.37 (p = 0.04)**

Table 5. Stop Straight Correlation Analysis Results

	Cognitive Domain Measures						
Measure	**EF**	**AF**	**WMF**	**ORR PF**	**PSF**	**MF**	**PV PF**
Vehicle Domain Measures							
BRTP	0.09 (p = 0.66)	0.34 (p = 0.09)	-0.30 (p = 0.14)	0.19 (p = 0.35)	0.25 (p = 0.22)	-0.04 (p = 0.84)	0.18 (p = 0.37)
BTP	-0.09 (p = 0.66)	-0.34 (p = 0.09)	0.30 (p = 0.14)	-0.19 (p = 0.35)	-0.25 (p = 0.22)	0.04 (p = 0.84)	-0.18 (p = 0.37)
BRDP	0.09 (p = 0.67)	0.37 (p = 0.06)	0.29 (p = 0.15)	0.20 (p = 0.33)	0.20 (p = 0.33)	0.03 (p = 0.90)	0.18 (p = 0.37)
BDP	-0.09 (p = 0.67)	-0.37 (p = 0.06)	-0.29 (p = 0.15)	-0.20 (p = 0.33)	-0.20 (p = 0.33)	-0.03 (p = 0.90)	-0.18 (p = 0.37)
Max Decel	-0.28 (p = 0.17)	0.06 (p = 0.79)	-0.05 (p = 0.80)	0.22 (p = 0.28)	-0.17 (p = 0.42)	0.29 (p = 0.16)	**0.40 (p = 0.04)**
Avg Decel	-0.21 (p = 0.31)	0.21 (p = 0.30)	-0.02 (p = 0.91)	0.19 (p = 0.35)	-0.21 (p = 0.31)	0.30 (p = 0.13)	**0.42 (p = 0.03)**
Min Jerk	0.21 (p = 0.30)	0.13 (p = 0.53)	0.15 (p = 0.46)	0.15 (p = 0.45)	0.32 (p = 0.12)	-0.17 (p = 0.40)	-0.13 (p = 0.54)
Avg Jerk	0.36 (p = 0.07)	0.16 (p = 0.44)	0.17 (p = 0.40)	0.25 (p = 0.22)	0.19 (p = 0.34)	0.20 (p = 0.33)	0.09 (p = 0.68)
Max Jerk	-0.10 (p = 0.63)	0.08 (p = 0.70)	0.00 (p = 0.99)	0.09 (p = 0.66)	-0.10 (p = 0.62)	0.11 (p = 0.58)	0.35 (p = 0.08)
Min Speed	**0.51 (p = 0.01)**	0.27 (p = 0.18)	0.31 (p = 0.12)	0.00 (p = 0.99)	0.12 (p = 0.56)	0.04 (p = 0.86)	-0.07 (p = 0.74)
Physiological Domain Measures							
Avg BR	0.18 (p = 0.39)	0.16 (p = 0.42)	0.23 (p = 0.26)	-0.08 (p = 0.70)	**0.42 (p = 0.03)**	-0.08 (p = 0.71)	-0.01 (p = 0.97)
Avg HR	0.26 (p = 0.21)	0.15 (p = 0.46)	0.38 (p = 0.06)	0.02 (p = 0.92)	0.18 (p = 0.39)	0.05 (p = 0.81)	0.06 (p = 0.78)
Avg HRV	-0.08 (p = 0.70)	0.10 (p = 0.64)	0.20 (p = 0.34)	0.23 (p = 0.26)	-0.08 (p = 0.68)	**0.23 (p = 0.27)**	0.40 (p = 0.04)
Avg GSR	-0.22 (p = 0.28)	-0.10 (p = 0.62)	0.00 (p = 0.99)	0.20 (p = 0.34)	-0.22 (p = 0.27)	0.04 (p = 0.85)	0.13 (p = 0.53)
Arousal	-0.03 (p = 0.89)	0.08 (p = 0.70)	0.29 (p = 0.15)	0.21 (p = 0.31)	-0.02 (p = 0.93)	**0.11 (p = 0.58)**	0.27 (p = 0.17)
Avg Arousal	-0.03 (p = 0.89)	0.08 (p = 0.70)	0.29 (p = 0.15)	0.21 (p = 0.31)	-0.02 (p = 0.94)	**0.11 (p = 0.58)**	0.27 (p = 0.17)

Table 6. TL Red Right Correlation Analysis Results

	Cognitive Domain Measures						
Measure	**EF**	**AF**	**WMF**	**ORR PF**	**PSF**	**MF**	**PV PF**
Vehicle Domain Measures							
BRTP	0.28 (p = 0.11)	0.28 (p = 0.12)	-0.27 (p = 0.12)	**0.36 (p = 0.04)**	0.30 (p = 0.09)	0.25 (p = 0.16)	0.22 (p = 0.23)
BTP	-0.28 (p = 0.11)	-0.28 (p = 0.12)	0.27 (p = 0.12)	**-0.36 (p = 0.04)**	-0.30 (p = 0.09)	0.25 (p = 0.16)	-0.22 (p = 0.23)
BRDP	0.20 (p = 0.27)	0.23 (p = 0.20)	0.30 (p = 0.09)	**0.36 (p = 0.04)**	0.27 (p = 0.13)	0.31 (p = 0.08)	0.24 (p = 0.19)
BDP	-0.20 (p = 0.27)	-0.23 (p = 0.20)	-0.30 (p = 0.09)	**-0.36 (p = 0.04)**	-0.27 (p = 0.13)	-0.31 (p = 0.08)	-0.24 (p = 0.19)
Max Decel	-0.40 (p = 0.02)	-0.22 (p = 0.21)	-0.10 (p = 0.57)	-0.09 (p = 0.62)	-0.10 (p = 0.57)	-0.03 (p = 0.85)	-0.13 (p = 0.46)
Avg Decel	-0.33 (p = 0.06)	-0.14 (p = 0.43)	-0.09 (p = 0.62)	0.03 (p = 0.85)	-0.03 (p = 0.86)	0.02 (p = 0.93)	-0.10 (p = 0.58)
Min Jerk	-0.09 (p = 0.63)	-0.05 (p = 0.78)	-0.04 (p = 0.83)	0.10 (p = 0.57)	-0.03 (p = 0.86)	0.01 (p = 0.96)	-0.08 (p = 0.64)
Avg Jerk	0.07 (p = 0.70)	0.06 (p = 0.74)	-0.07 (p = 0.68)	0.07 (p = 0.69)	-0.08 (p = 0.65)	0.08 (p = 0.67)	-0.08 (p = 0.64)
Max Jerk	-0.27 (p = 0.12)	0.17 (p = 0.34)	-0.17 (p = 0.33)	0.14 (p = 0.43)	0.12 (p = 0.51)	0.08 (p = 0.67)	-0.04 (p = 0.83)
Min Speed	0.04 (p = 0.81)	0.21 (p = 0.24)	0.13 (p = 0.47)	-0.12 (p = 0.51)	-0.04 (p = 0.81)	-0.07 (p = 0.71)	-0.15 (p = 0.41)
Physiological Domain Measures							
Avg BR	0.22 (p = 0.22)	0.11 (p = 0.52)	-0.02 (p = 0.92)	-0.17 (p = 0.35)	**0.43 (p = 0.01)**	-0.08 (p = 0.66)	-0.19 (p = 0.29)
Avg HR	-0.03 (p = 0.89)	0.20 (p = 0.27)	**0.43 (p = 0.01)**	0.02 (p = 0.93)	-0.12 (p = 0.50)	0.12 (p = 0.52)	0.12 (p = 0.50)
Avg HRV	-0.18 (p = 0.31)	-0.17 (p = 0.35)	-0.01 (p = 0.94)	0.10 (p = 0.59)	0.01 (p = 0.97)	-0.03 (p = 0.85)	-0.03 (p = 0.87)
Avg GSR	0.05 (p = 0.78)	0.13 (p = 0.48)	0.19 (p = 0.29)	**0.34 (p = 0.05)**	-0.06 (p = 0.74)	0.04 (p = 0.81)	0.11 (p = 0.56)
Arousal	0.03 (p = 0.87)	0.14 (p = 0.48)	0.28 (p = 0.11)	0.18 (p = 0.31)	0.04 (p = 0.82)	0.04 (p = 0.81)	0.05 (p = 0.79)
Avg Arousal	0.03 (p = 0.88)	0.14 (p = 0.48)	0.28 (p = 0.11)	0.18 (p = 0.31)	0.04 (p = 0.82)	0.04 (p = 0.81)	0.05 (p = 0.79)

Table 7. TL Red Left Correlation Analysis Results

	Cognitive Domain Measures						
Measure	**EF**	**AF**	**WMF**	**ORR PF**	**PSF**	**MF**	**PV PF**
Vehicle Domain Measures							
BRTP	-0.08 (p = 0.64)	0.02 (p = 0.90)	0.26 (p = 0.14)	0.17 (p = 0.34)	0.01 (p = 0.96)	0.03 (p = 0.85)	0.28 (p = 0.11)
BTP	0.08 (p = 0.64)	-0.02 (p = 0.90)	-0.26 (p = 0.14)	-0.17 (p = 0.34)	-0.01 (p = 0.96)	-0.03 (p = 0.85)	-0.28 (p = 0.11)
BRDP	-0.16 (p = 0.37)	0.06 (p = 0.76)	0.23 (p = 0.19)	0.11 (p = 0.52)	0.01 (p = 0.96)	0.06 (p = 0.74)	0.26 (p = 0.14)
BDP	0.16 (p = 0.37)	-0.06 (p = 0.76)	-0.23 (p = 0.19)	-0.11 (p = 0.52)	-0.01 (p = 0.96)	-0.06 (p = 0.74)	-0.26 (p = 0.14)
Max Decel	0.03 (p = 0.88)	-0.03 (p = 0.86)	-0.06 (p = 0.75)	0.06 (p = 0.73)	0.02 (p = 0.89)	**0.44 (p = 0.01)**	0.02 (p = 0.93)
Avg Decel	-0.14 (p = 0.42)	-0.04 (p = 0.84)	-0.27 (p = 0.12)	0.00 (p = 0.99)	0.09 (p = 0.61)	**0.44 (p = 0.01)**	-0.14 (p = 0.43)
Min Jerk	-0.24 (p = 0.18)	-0.05 (p = 0.79)	-0.22 (p = 0.21)	0.06 (p = 0.74)	0.03 (p = 0.86)	-0.07 (p = 0.70)	-0.15 (p = 0.40)
Avg Jerk	-0.24 (p = 0.17)	-0.04 (p = 0.84)	-0.01 (p = 0.95)	-0.03 (p = 0.85)	-0.15 (p = 0.40)	0.07 (p = 0.70)	-0.03 (p = 0.85)
Max Jerk	0.02 (p = 0.91)	0.19 (p = 0.28)	-0.22 (p = 0.22)	0.14 (p = 0.43)	0.03 (p = 0.87)	0.31 (p = 0.07)	0.10 (p = 0.57)
Physiological Domain Measures							
Avg BR	0.20 (p = 0.26)	0.01 (p = 0.96)	0.00 (p = 0.99)	-0.29 (p = 0.10)	0.31 (p = 0.07)	-0.21 (p = 0.24)	-0.31 (p = 0.07)
Avg HR	-0.02 (p = 0.93)	0.33 (p = 0.06)	**0.54 (p = 0.00)**	0.10 (p = 0.59)	-0.21 (p = 0.23)	0.21 (p = 0.24)	0.32 (p = 0.06)
Avg HRV	0.05 (p = 0.77)	**0.34 (p = 0.05)**	0.06 (p = 0.72)	0.29 (p = 0.09)	-0.10 (p = 0.56)	0.24 (p = 0.17)	0.28 (p = 0.11)
Avg GSR	0.06 (p = 0.72)	0.07 (p = 0.68)	0.29 (p = 0.09)	**0.35 (p = 0.05)**	-0.11 (p = 0.52)	0.11 (p = 0.54)	0.22 (p = 0.22)
Arousal	0.13 (p = 0.47)	**0.34 (p = 0.05)**	**0.46 (p = 0.01)**	0.29 (p = 0.10)	-0.10 (p = 0.57)	0.19 (p = 0.27)	0.29 (p = 0.09)
Avg Arousal	0.13 (p = 0.47)	**0.34 (p = 0.05)**	**0.46 (p = 0.01)**	0.29 (p = 0.10)	-0.10 (p = 0.57)	0.19 (p = 0.27)	0.29 (p = 0.00)

Table 8. TL Red Straight Correlation Analysis Results

	Cognitive Domain Measures						
Measure	**EF**	**AF**	**WMF**	**ORR PF**	**PSF**	**MF**	**PV PF**
Vehicle Domain Measures							
BRTP	0.15 (p = 0.38)	0.06 (p = 0.74)	-0.18 (p = 0.28)	0.12 (p = 0.49)	0.04 (p = 0.81)	0.05 (p = 0.77)	0.21 (p = 0.21)
BTP	-0.15 (p = 0.38)	-0.06 (p = 0.74)	0.18 (p = 0.28)	-0.12 (p = 0.49)	-0.04 (p = 0.81)	-0.05 (p = 0.77)	-0.21 (p = 0.21)
BRDP	0.13 (p = 0.4)	0.15 (p = 0.39)	0.12 (p = 0.48)	0.14 (p = 0.42)	0.03 (p = 0.88)	0.12 (p = 0.48)	0.27 (p = 0.12)
BDP	-0.13 (p = 0.44)	-0.15 (p = 0.39)	-0.12 (p = 0.48)	-0.14 (p = 0.42)	-0.03 (p = 0.88)	-0.12 (p = 0.48)	-0.27 (p = 0.12)
Max Decel	**-0.37** **(p = 0.03)**	-0.27 (p = 0.11)	-0.22 (p = 0.19)	-0.08 (p = 0.66)	-0.08 (p = 0.64)	0.14 (p = 0.42)	-0.15 (p = 0.37)
Avg Decel	-0.28 (p = 0.10)	-0.06 (p = 0.73)	-0.21 (p = 0.21)	0.02 (p = 0.90)	-0.05 (p = 0.78)	0.22 (p = 0.20)	-0.11 (p = 0.52)
Min Jerk	0.06 (p = 0.73)	0.20 (p = 0.23)	0.04 (p = 0.81)	0.07 (p = 0.67)	0.02 (p = 0.90)	0.21 (p = 0.23)	0.04 (p = 0.82)
Avg Jerk	-0.24 (p = 0.15)	-0.06 (p = 0.75)	-0.27 (p = 0.12)	0.11 (p = 0.51)	-0.27 (p = 0.12)	-0.13 (p = 0.46)	0.06 (p = 0.73)
Max Jerk	-0.14 (p = 0.42)	-0.03 (p = 0.85)	**-0.35** **(p = 0.03)**	0.04 (p = 0.80)	0.02 (p = 0.92)	-0.02 (p = 0.93)	-0.10 (p = 0.57)
Physiological Domain Measures							
Avg BR	0.19 (p = 0.26)	-0.01 (p = 0.94)	-0.04 (p = 0.83)	**-0.31** **(p = 0.06)**	**0.37** **(p = 0.03)**	-0.23 (p = 0.17)	-0.25 (p = 0.14)
Avg HR	0.05 (p = 0.78)	0.26 (p = 0.12)	**0.37** **(p = 0.02)**	0.08 (p = 0.63)	-0.11 (p = 0.54)	0.11 (p = 0.51)	0.11 (p = 0.52)
Avg HRV	-0.02 (p = 0.90)	0.10 (p = 0.57)	0.14 (p = 0.41)	0.18 (p = 0.30)	-0.13 (p = 0.45)	0.25 (p = 0.14)	**0.33** **(p = 0.05)**
Avg GSR	0.02 (p = 0.92)	0.05 (p = 0.76)	0.14 (p = 0.41)	**0.35** **(p = 0.04)**	-0.13 (p = 0.45)	0.08 (p = 0.64)	0.18 (p = 0.29)
Arousal	0.09 (p = 0.60)	0.21 (p = 0.23)	**0.41** **(p = 0.01)**	0.27 (p = 0.11)	-0.08 (p = 0.63)	0.15 (p = 0.38)	0.25 (p = 0.14)
Avg Arousal	0.09 (p = 0.60)	0.21 (p = 0.23)	**0.41** **(p = 0.01)**	0.27 (p = 0.11)	-0.08 (p = 0.63)	0.15 (p = 0.38)	0.25 (p = 0.14)

Table 9. Stop Correlation Analysis Results

	Cognitive Domain Measures						
Measure	**EF**	**AF**	**WMF**	**ORR PF**	**PSF**	**MF**	**PV PF**
Vehicle Domain Measures							
BRTP	0.14 (p = 0.42)	0.16 (p = 0.35)	-0.03 (p = 0.87)	0.24 (p = 0.26)	0.12 (p = 0.49)	0.05 (p = 0.78)	0.07 (p = 0.67)
BTP	-0.14 (p = 0.42)	-0.16 (p = 0.35)	0.03 (p = 0.87)	-0.24 (p = 0.16)	-0.12 (p = 0.49)	-0.05 (p = 0.78)	-0.07 (p = 0.67)
BRDP	0.07 (p = 0.70)	0.17 (p = 0.32)	0.02 (p = 0.91)	0.26 (p = 0.13)	0.01 (p = 0.95)	0.12 (p = 0.49)	0.12 (p = 0.47)
BDP	-0.07 (p = 0.70)	-0.17 (p = 0.32)	-0.02 (p = 0.91)	-0.26 (p = 0.13)	-0.01 (p = 0.95)	-0.12 (p = 0.49)	-0.12 (p = 0.47)
Max Decel	-0.26 (p = 0.12)	-0.04 (p = 0.79)	-0.22 (p = 0.19)	-0.07 (p = 0.70)	-0.15 (p = 0.37)	0.08 (p = 0.62)	0.04 (p = 0.82)
Avg Decel	-0.24 (p = 0.15)	0.01 (p = 0.95)	-0.25 (p = 0.13)	-0.14 (p = 0.41)	-0.10 (p = 0.57)	0.10 (p = 0.56)	-0.04 (p = 0.82)
Min Jerk	0.08 (p = 0.65)	0.18 (p = 0.30)	-0.02 (p = 0.90)	-0.17 (p = 0.32)	0.15 (p = 0.38)	-0.04 (p = 0.83)	-0.08 (p = 0.65)
Avg Jerk	-0.05 (p = 0.78)	-0.04 (p = 0.79)	-0.22 (p = 0.19)	0.05 (p = 0.76)	-0.11 (p = 0.53)	-0.08 (p = 0.64)	-0.12 (p = 0.48)
Max Jerk	-0.05 (p = 0.75)	-0.03 (p = 0.86)	-0.16 (p = 0.34)	-0.05 (p = 0.75)	-0.02 (p = 0.92)	0.03 (p = 0.87)	-0.05 (p = 0.75)
Min Speed	0.17 (p = 0.32)	0.13 (p = 0.44)	0.10 (p = 0.55)	0.07 (p = 0.70)	0.19 (p = 0.25)	0.00 (p = 1.00)	0.04 (p = 0.80)
Physiological Domain Measures							
Avg BR	0.20 (p = 0.24)	0.14 (p = 0.41)	0.23 (p = 0.17)	-0.17 (p = 0.31)	**0.51 (p = 0.00)**	0.00 (p = 1.00)	-0.14 (p = 0.40)
Avg HR	0.00 (p = 1.00)	0.25 (p = 0.13)	**0.40 (p = 0.01)**	0.03 (p = 0.88)	-0.07 (p = 0.70)	0.10 (p = 0.55)	0.20 (p = 0.23)
Avg HRV	-0.12 (p = 0.46)	-0.05 (p = 0.75)	0.19 (p = 0.26)	0.20 (p = 0.23)	-0.15 (p = 0.37)	0.24 (p = 0.16)	**0.54 (p = 0.00)**
Avg GSR	0.05 (p = 0.76)	0.00 (p = 0.99)	0.23 (p = 0.18)	0.30 (p = 0.07)	-0.12 (p = 0.46)	0.05 (p = 0.76)	0.20 (p = 0.23)
Arousal	0.03 (p = 0.87)	0.11 (p = 0.50)	**0.45 (p = 0.01)**	0.24 (p = 0.15)	-0.04 (p = 0.83)	0.18 (p = 0.29)	**0.41 (p = 0.01)**
Avg Arousal	0.03 (p = 0.87)	0.11 (p = 0.50)	**0.45 (p = 0.01)**	0.24 (p = 0.15)	-0.04 (p = 0.83)	0.18 (p = 0.29)	**0.41 (p = 0.01)**

Results from this experiment shows that there was no significant correlation found between any of the vehicle measures and cognitive functions. On the contrary in most of the scenarios physiological measures were found significantly correlated with cognitive functions. One thing to note here is that for TL Red Left and TL Red Straight cases minimum speed was not used as a performance measure as driver must make a complete stop for these two scenarios.

Working memory and Picture Vocabulary functions were found most significant with driving behavior measures in physiological domains. For more stronger conclusion the same experiment can be generated on much larger dataset to determine the cognitive function highly related to driving behavior difference between different drivers.

2. T-Test Analysis

Based on the drivers' cognitive abilities they were classified either in MCI or Non-MCI groups. This grouping was performed by the experts in the field. One thing to note here is that not all the MCI drivers possess declined cognitive abilities in all the domains. From Figure 5(a-g) it was clear that one driver may possess significant declination in only one domain. Other drivers may show declination in one or more domains, but declination may not be significant in both domains. There are a lot of different combinations possible.

Importance of this experiment is to be able to find statistical difference between driving performance measures in both the groups. In order to do so first the data was classified in two groups and then T-test was performed on each driving performance measure. No outlier detection methods were applied to the data since this experiment was conducted to find statistical difference between two groups of driving performance measures in both vehicle domain and physiological domain. Based on the T-test results significantly different measures were identified using probability threshold of 0.05 or less.

This experiment was conducted in order to support the machine learning models. Based on the results of this experiments it was determined if there is any machine learning approach that can be implied on the driving performance measures to classify the driver using the measures or not. As the dataset was smaller in size neural network cannot be trained as neural networks do not work well with smaller data sets and tend to overfit easily with smaller datasets. Results of this experiments provided major information about which driving performance measures were significantly different in both the groups.

There was no research done with the measures that I have used in this study and for that reason I have used a total of 22 measures in this experiment. Here is a list of measures that I have used,

- Vehicle Domain Measures:
    - Brake Reaction Time (BRT)

  - Brake Time (BT)
  - Decelerating Time (DT)
  - Brake Reaction Distance (BRD)
  - Brake Distance (BD)
  - Decelerating Distance (DD)
  - Brake Reaction Time Percentage (BRTP)
  - Brake Time Percentage (BTP)
  - Brake Reaction Distance Percentage (BRDP)
  - Brake Distance Percentage (BDP)
  - Maximum Deceleration (Max Decel)
  - Average Deceleration (Avg Decel)
  - Minimum Jerk (Min Jerk)
  - Average Jerk (Avg Jerk)
  - Maximum Jerk (Max Jerk)
  - Minimum Speed (Min Speed)
- Physiological Domain Measures:
  - Average BR during Brake Time (Avg BR)
  - Average HR during Brake Time (Avg HR)
  - Average HRV during Brake Time (Avg HRV)
  - Average GSR during Brake Time (Avg GSR)
  - Arousal Level during Brake Time (Arousal)
  - Average Arousal Level during Brake Time (Avg Arousal)

One thing to note here is that for TL Red Left and TL Red Straight cases minimum speed measure was not used since in both these scenarios driver must make a complete stop. T-test results are mentioned in Table 10 to 16. Table 1 represents the total samples for each group for all the different intersection scenarios used.

Table 10. Stop Right T-test Results

Measure	Mean ± STD MCI	Mean ± STD Non-MCI	Hypothesis	p_value
Vehicle Domain Measures				
BRT	3.67±3.14	3.61±6.73	0	0.92
BT	11.35±5.12	10.48±7.54	0	0.21
DT	15.01±7.31	14.09±13.72	0	0.45
BRD	31.71±33.65	30.15±38.36	0	0.68
BD	51.91±50.01	49.72±58.48	0	0.70
DD	80.83±68.49	75.13±77.71	0	0.46
BRTP	0.19±0.22	0.22±0.19	0	0.28
BTP	0.81±0.22	0.78±0.19	0	0.28
BRDP	0.26±0.24	0.31±0.22	0	0.12
BDP	0.74±0.24	0.69±0.22	0	0.12
Max Decel	2.09±0.79	2.25±0.72	0	0.11
Avg Decel	0.99±0.42	1.09±0.38	0	0.06
Min Jerk	**-5.03±2.48**	**-4.15±2.10**	**1**	**0.00**
Avg Jerk	0.08±0.07	0.07±0.26	0	0.68
Max Jerk	7.35±4.36	7.86±3,69	0	0.34
Min Speed	1.65±1.92	1.99±3.60	0	0.45
Physiological Domain Measures				
Avg BR	**0.39±0.15**	**0.33±0.13**	**1**	**0.00**
Avg HR	0.42±0.18	0.40±0.16	0	0.41
Avg HRV	0.71±0.21	0.70±0.19	0	0.82
Avg GSR	0.74±0.24	0.78±0.26	0	0.24
Arousal	0.56±0.11	0.55±0.10	0	0.53
Avg Arousal	0.56±0.11	0.55±0.10	0	0.52

Table 11. Stop Left T-test Results

Measure	Mean ± STD MCI	Mean ± STD Non-MCI	Hypothesis	p_value
Vehicle Domain Measures				
BRT	3.28±3.21	3.58±4.79	0	0.54
BT	12.08±5.99	11.52±6.34	0	0.44
DT	15.36±8.11	15.10±10.24	0	0.81
BRD	30.97±31.51	32.51±38.03	0	0.71
BD	69.58±79.73	66.95±150.79	0	0.86
DD	94.49±88.60	90.73±81.35	0	0.71
BRTP	0.19±0.22	0.17±0.19	0	0.48
BTP	0.81±0.22	0.83±0.19	0	0.48
BRDP	0.25±0.22	0.25±0.21	0	0.94
BDP	0.75±0.22	0.75±0.21	0	0.94
Max Decel	1.91±0.59	2.03±0.60	0	0.09
Avg Decel	**0.91±0.36**	**1.07±0.37**	**1**	**0.00**
Min Jerk	**-4.66±2.29**	**-3.65±1.57**	**1**	**0.00**
Avg Jerk	0.08±0.11	0.09±0.25	0	0.60
Max Jerk	6.67±2.75	6.62±3.02	0	0.90
Min Speed	**0.78±1.55**	**0.53±0.76**	**1**	**0.05**
Physiological Domain Measures				
Avg BR	**0.40±0.14**	**0.31±0.12**	**1**	**0.00**
Avg HR	0.38±0.19	0.39±0.16	0	0.54
Avg HRV	**0.67±0.23**	**0.74±0.19**	**1**	**0.01**
Avg GSR	**0.74±0.26**	**0.82±0.22**	**1**	**0.01**
Arousal	0.55±0.11	0.57±0.09	0	0.23
Avg Arousal	0.55±0.11	0.57±0.09	0	0.22

Table 12. Stop Straight T-test Results

Measure	Mean ± STD MCI	Mean ± STD Non-MCI	Hypothesis	p_value
Vehicle Domain Measures				
BRT	3.10±2.49	2.65±2.09	0	0.08
BT	**7.80±4.13**	**10.45±10.26**	**1**	**0.00**
DT	**10.90±4.78**	**13.10±11.30**	**1**	**0.03**
BRD	33.22±29.36	35.72±32.90	0	0.48
BD	**64.07±70.15**	**105.27±198.24**	**1**	**0.02**
DD	**96.33±82.62**	**131.28±114.45**	**1**	**0.00**
BRTP	0.17±0.17	0.17±0.16	0	0.98
BTP	0.83±0.17	0.83±0.16	0	0.98
BRDP	0.25±0.20	0.26±0.19	0	0.79
BDP	0.75±0.20	0.74±0.19	0	0.79
Max Decel	**1.98±0.67**	**2.09±0.58**	**1**	**0.01**
Avg Decel	**0.98±0.38**	**1.10±0.37**	**1**	**0.00**
Min Jerk	**-4.50±2.43**	**-3.78±1.61**	**1**	**0.00**
Avg Jerk	0.06±0.12	0.06±0.14	0	0.73
Max Jerk	**6.77±3.27**	**6.32±2.88**	**1**	**0.03**
Min Speed	0.61±0.56	0.84±2.75	0	0.15
Physiological Domain Measures				
Avg BR	**0.38±0.13**	**0.31±0.13**	**1**	**0.00**
Avg HR	**0.42±0.21**	**0.40±0.17**	**1**	**0.03**
Avg HRV	0.74±0.21	0.74±0.20	0	0.88
Avg GSR	**0.71±0.26**	**0.78±0.26**	**1**	**0.00**
Arousal	0.56±0.11	0.56±0.10	0	0.30
Avg Arousal	0.56±0.11	0.56±0.10	0	0.30

Table 13. TL Red Right T-test Results

Measure	Mean ± STD MCI	Mean ± STD Non-MCI	Hypothesis	p_value
Vehicle Domain Measures				
BRT	3.43±5.70	4.29±13.25	0	0.60
BT	12.02±6.47	11.44±5.46	0	0.47
DT	15.45±7.24	15.73±13.19	0	0.86
BRD	**27.71±25.05**	**40.14±43.10**	**1**	**0.02**
BD	95.01±94.98	98.53±78.07	0	0.76
DD	129±108.96	146.77±100.86	0	0.22
BRTP	0.19±0.22	0.22±0.19	0	0.28
BTP	0.81±0.22	0.78±0.19	0	0.28
BRDP	0.26±0.24	0.31±0.22	0	0.12
BDP	0.74±0.24	0.69±0.22	0	0.12
Max Decel	2.09±0.79	2.25±0.72	0	0.11
Avg Decel	0.99±0.42	1.09±0.38	0	0.06
Min Jerk	**-5.03±2.48**	**-4.15±2.10**	**1**	**0.00**
Avg Jerk	0.08±0.07	0.07±0.26	0	0.68
Max Jerk	7.35±4.36	7.86±3.69	0	0.34
Min Speed	1.65±1.92	1.99±3.60	0	0.45
Physiological Domain Measures				
Avg BR	**0.39±0.15**	**0.33±0.13**	**1**	**0.00**
Avg HR	0.42±0.18	0.40±0.16	0	0.41
Avg HRV	0.71±0.21	0.70±0.19	0	0.82
Avg GSR	0.74±0.24	0.78±0.26	0	0.24
Arousal	0.56±0.11	0.55±0.10	0	0.53
Avg Arousal	0.56±0.11	0.55±0.10	0	0.52

Table 14. TL Red Left T-test Results

Measure	**Mean ± STD MCI**	**Mean ± STD Non-MCI**	**Hypothesis**	**p_value**
Vehicle Domain Measures				
BRT	4.75±14.40	2.73±5.06	0	0.06
BT	13.50±8.32	12.00±6.93	0	0.10
DT	**18.25±15.33**	**14.73±7.62**	**1**	**0.01**
BRD	30.52±37.78	27.07±26.77	0	0.35
BD	114.50±127.92	106.51±118.07	0	0.59
DD	178.31±208.03	167.62±176.66	0	0.64
BRTP	0.19±0.22	0.17±0.19	0	0.48
BTP	0.81±0.22	0.83±0.19	0	0.48
BRDP	0.25±0.22	0.25±0.21	0	0.94
BDP	0.75±0.22	0.75±0.21	0	0.94
Max Decel	1.91±0.59	2.03±0.60	0	0.09
Avg Decel	**0.91±0.36**	**1.07±0.37**	**1**	**0.00**
Min Jerk	**-4.66±2.29**	**-3.65±1.57**	**1**	**0.00**
Avg Jerk	0.08±0.11	0.09±0.25	0	0.60
Max Jerk	6.67±2.75	6.62±3.02	0	0.90
Physiological Domain Measures				
Avg BR	**0.40±0.14**	**0.31±0.12**	**1**	**0.00**
Avg HR	0.38±0.19	0.39±0.16	0	0.54
Avg HRV	**0.67±0.23**	**0.74±0.19**	**1**	**0.01**
Avg GSR	**0.74±0.26**	**0.82±0.22**	**1**	**0.01**
Arousal	0.55±0.11	0.57±0.09	0	0.22
Avg Arousal	0.55±0.11	0.57±0.09	0	0.23

Table 15. TL Red Straight T-test Results

Measure	Mean ± STD MCI	Mean ± STD Non-MCI	Hypothesis	p_value
Vehicle Domain Measures				
BRT	3.83±12.20	3.20±10.95	0	0.41
BT	**15.41±8.84**	**13.73±8.25**	**1**	**0.00**
DT	**19.25±14.51**	**16.93±13.36**	**1**	**0.01**
BRD	40.89±63.36	38.56±62.77	0	0.58
BD	133.09±124.81	121.63±123.96	0	0.17
DD	203.66±222.57	208.65±266.94	0	0.77
BRTP	0.17±0.17	0.17±0.16	0	0.98
BTP	0.83±0.17	0.83±0.16	0	0.98
BRDP	0.25±0.20	0.26±0.19	0	0.79
BDP	0.75±0.20	0.74±0.19	0	0.79
Max Decel	**1.98±0.67**	**2.09±0.58**	**1**	**0.01**
Avg Decel	**0.98±0.38**	**1.10±0.37**	**1**	**0.00**
Min Jerk	**-4.50±2.43**	**-3.78±1.61**	**1**	**0.00**
Avg Jerk	0.06±0.12	0.06±0.14	0	0.73
Max Jerk	**6.77±3.27**	**6.32±2.88**	**1**	**0.03**
Physiological Domain Measures				
Avg BR	**0.38±0.13**	**0.31±0.13**	**1**	**0.00**
Avg HR	**0.42±0.21**	**0.40±0.17**	**1**	**0.03**
Avg HRV	0.74±0.21	0.74±0.20	0	0.88
Avg GSR	**0.71±0.26**	**0.78±0.26**	**1**	**0.00**
Arousal	0.56±0.11	0.56±0.10	0	0.30
Avg Arousal	0.56±0.11	0.56±0.10	0	0.30

Table 16. Stop T-test Results

Measure	Mean ± STD MCI	Mean ± STD Non-MCI	Hypothesis	p_value
Vehicle Domain Measures				
BRT	3.35±2.95	3.34±5.29	0	0.95
BT	10.32±5.42	10.76±8.10	0	0.33
DT	13.67±7.10	14.09±12.20	0	0.52
BRD	32.02±31.48	32.33±36.86	0	0.89
BD	61.52±67.43	69.71±137.96	0	0.26
DD	90.40±80.09	94.84±93.03	0	0.43
BRTP	**0.23±0.15**	**0.21±0.13**	**1**	**0.04**
BTP	**0.77±0.15**	**0.79±0.13**	**1**	**0.04**
BRDP	0.37±0.23	0.36±0.22	0	0.56
BDP	0.63±0.23	0.64±0.22	0	0.56
Max Decel	**2.09±0.72**	**2.26±0.70**	**1**	**0.00**
Avg Decel	**1.04±0.41**	**1.15±0.43**	**1**	**0.00**
Min Jerk	**-4.35±2.07**	**-4.05±2.15**	**1**	**0.02**
Avg Jerk	0.11±0.20	0.14±0.32	0	0.10
Max Jerk	**7.79±3.49**	**8.56±4.20**	**1**	**0.00**
Min Speed	4.10±7.97	4.09±11.38	0	0.98
Physiological Domain Measures				
Avg BR	**0.37±0.13**	**0.31±0.13**	**1**	**0.00**
Avg HR	0.41±0.20	0.39±0.17	0	0.13
Avg HRV	0.65±0.22	0.66±0.23	0	0.34
Avg GSR	**0.68±0.25**	**0.75±0.26**	**1**	**0.00**
Arousal	0.53±0.12	0.53±0.11	0	0.77
Avg Arousal	0.53±0.12	0.53±0.11	0	0.77

T-test results showed that in all the 7 intersection scenarios Average BR during brake time showed the significant difference between both the classes. Minimum jerk showed the significant difference in both the groups as well. MCI group of drivers showed higher level of jerk while applying the brakes as well which clearly shows higher rate of change of acceleration and or deceleration is significantly different in MCI and Non-MCI group of drivers. MCI drivers tend to have higher rate of change of deceleration. Due to slow responsiveness MCI drivers apply brakes hard enough to make a complete stop at intersection. Due the fact drivers apply hard brakes their natural breathing pattern increases due to higher level of stress. But their maximum deceleration rate is not for a longer period due to this fact rate of change of deceleration was found most important measure to identify significant difference between MCI and Non-MCI group of drivers.

3. Stopping percentage analysis between MCI and Non-MCI group

It was well known that MCI drivers tend to respond slowly as compared to Non-MCI group of drivers, it was found important to understand if slower responsiveness can cause major threats to MCI drivers or not. In order to obey the traffic rules drivers must be able to comply with the stopping standards at stop signs for a safe pass through the intersection. In order to determine if the driver has made a complete stop at intersection or not, minimum speed threshold of 1mph or less was used. Due physical restriction while collecting the data minimum speed was found to be near to 0 but not exactly 0 and for that reason threshold was used to determine if the driver has made a complete stop or not.

Devlin et al [14] determined that MCI drivers don't tend to stop at intersections with stop sign. But according to [9] naturalistic driving behavior was found totally different as compared to simulation driving. In simulation driving driver may have an influence of being aware about driving in simulator environment. This experiment was conducted to understand the compliance of MCI drivers with stop sign as compared to Non-MCI group of drivers.

At first all the samples were separated based on respective drivers' class (MCI and Non-MCI). After that total samples identified with minimum speed less than 1 mph. Stopping percentage was calculated as:

$$StoppingPercent = \frac{Total\,Samples\,with\,minimum\,speed < 1mph}{Total\,number\,of\,samples}$$

This experiment was conducted for 5 different intersection scenarios. These scenarios as follows,

1. Stop sign with driver wants to take right turn (Stop Right)
2. Stop sign with driver wants to take left turn (Stop Left)
3. Stop sign with driver wants to go straight (Stop Straight)
4. Traffic light red with driver wants to take right turn (TL Red Right)
5. Stop sign (Stop)

It should be noted that as in United States most of the intersections with traffic light have a free right of way in which drivers are required to stop and then pass through the intersection. For that reason, TL_Red_Right case was also included in this experiment to determine the driver's compliance to make a stop when required by law to do so. Results of this experiment were represented in Table 17.

Table 17. Stopping Percentage Analysis Results

Intersection Scenario	Stopping Percentage (MCI)	Stopping Percentage (Non-MCI)
Stop Right	17.69%	20.80%
Stop Left	28.91%	34.13%
Stop Straight	8.72%	11.38%
TL Red Right	54.29%	62.37%
Stop	17.92%	21.88%

Results of this experiment comply with the results of Devlin using simulator data. Apart from that is can be observed that at traffic light red scenarios the driver tends to stop more often as compared to stop sign scenarios. For all the 5 scenarios analysed in this experiment shows that MCI drivers are more likely not to comply with the stop sign and traffic light as compared to Non-MCI drivers.

4. SVM Classification Model

This experiment was conducted to build a model that can classify the driver between MCI and Non-MCI group using driving performance measures with and without physiological measures extracted during brake application of drivers. At the end of this experiment I will propose a model that can classify driver in MCI or Non-MCI group. This model can be used to detect driver's current state and based on that assistive features can be turned on if driver resides in MCI group. It is assumed that driver may have MCI behavior due to several reasons such as driver forgot to take medication, driver didn't have enough sleep, et. For shorter time period the driver may need more assistance while driving. This model will be trained on a smaller data set but it will at least provide basic information on if this is possible or not with a large amount of dataset. Since the data set size was not too large extensive machine learning methods cannot be applied on the data and for that reason support vector machine (SVM) was chosen as SVM can fit a smaller data set well. There was a total of 5 models built based on the different measures used to train and test the SVM model. The data set was segregated using stratified sampling. As the dataset used was smaller in size 10-fold cross validation was applied on all the models. The models were then fine-tuned by changing the penalty factor to achieve better performance. List of models trained can be found in Table 18.

Table 18. SVM Model List

Model ID	Measures Used in Training and Testing
SVM Vehicle	Vehicle Measures
SVM Normalized	Normalized Measures with other Vehicle Measures
SVM Physiological	Physiological Measures
SVM PV	Physiological Measures with Vehicle Measures
SVM PN	Physiological Measures with Normalized Vehicle Measures

Here, normalized measures include all the time and distance domain measures with deceleration, jerk and minimum speed measures. Like other experiments for TL Red Left and TL Red Straight minimum speed measure was not used in training nor testing.

As there were multiple models trained with different penalty factors, I will explain the flow of how the results were achieved and there after I will present the best models that I chose based on the best results achieved using a specific set of data. All the models were trained on all 7 intersection scenarios mentioned in earlier sections.

First all the models were trained on different datasets with default penalty factor and penalty was gradually increased to specific level. Total of 5 penalty levels were chosen at random to achieve global maxima for average accuracy over all the 10 folds. The penalty levels were 1,2,5,10,50. All the models with different penalty levels were trained on same 10 folds. In order to find the best performance, first all the variables were used to train the SVM and average performance over 10 folds was achieved for all the penalty levels. After that each variable was removed one by one and if any combination performs better or match the average performance as of using all the variables, it was then used as a benchmark and experiment was repeated for all the intersection scenarios and all the penalty levels. In the following table I have represented the best results achieved once all the models were trained and tested for all the combinations mentioned above.

Table 19. SVM Vehicle Performance

Model ID	Best Performance	Penalty Level
Stop Right	65.83	50
Stop Left	59.4	5
Stop Straight	65.39	2
Combined Stop	60.76	50
TL Red Right	**74.21**	**50**
TL Red Left	75.52	50
TL Red Straight	68.57	10

Table 20. SVM Normalized Performance

Model ID	Best Performance	Penalty Level
Stop Right	65.08	50
Stop Left	59.37	50
Stop Straight	62.90	5
Combined Stop	60.76	50
TL Red Right	72.47	50
TL Red Left	71.65	5
TL Red Straight	66.42	5

Table 21. SVM Physiological Performance

Model ID	Best Performance	Penalty Level
Stop Right	65.08	50
Stop Left	63.47	50
Stop Straight	59.77	2
Combined Stop	60.07	10
TL Red Right	73.00	10
TL Red Left	71.61	10
TL Red Straight	66.32	10

Table 22. SVM PV Performance

Model ID	Best Performance	Penalty Level
Stop Right	70.2	10
Stop Left	**68.84**	**5**
Stop Straight	**67.28**	**1**
Combined Stop	66.37	5
TL Red Right	73.09	50
TL Red Left	**77.93**	**50**
TL Red Straight	**69.28**	**2**

Table 23. SVM PN Performance

Model ID	Best Performance	Penalty Level
Stop Right	**70.89**	**10**
Stop Left	68.4	50
Stop Straight	65.06	50
Combined Stop	**67.43**	**10**
TL Red Right	73.40	10
TL Red Left	74.95	10
TL Red Straight	68.68	10

The results showed better performance by combining both the physiological domain measures and vehicle domain measures. Since the dataset was smaller in size the model tends to overfit quickly. But as I have performed 10-fold cross validation if the model performs poor on one test set the accuracy of the model will gets affected. There were some cases where the model accuracy increases to a certain extend with increasing the penalty factor but with higher penalty factors the performance degraded. The best accuracy of the model was achieved at TL Red Left scenario by combining the physiological domain measures and vehicle domain measures. This machine learning experiment was performed to understand the capability of identifying MCI drivers and it turns out that simple machine learning algorithms can work well on this data. It should be noted here that the dataset used in this study may not represent the data for all the MCI group of drivers.

Chapter 5. Discussion

In this section first I will discuss the merits and demerits of new methods to extract the features from real world driving data. Next, I will discuss the important conclusions from the results of the experiments conducted.

I have developed the methods using which I was able to analyze drivers brake patterns. One of the main goals of this study was to understand the driver's behavior at intersection. Different researchers have used different measures using simulator data. Most of the measures cannot be extracted in real world due to many challenges such as unavailability of sensors, physical challenges in installing these sensors in vehicle, et cetera. Some of the measures can be extracted using different methods but the computational complexity may be too high for a vehicle. My main goal was to keep the measures as simple as possible so that implementation can be easy and feasible. In this data I have used the manual labeling that can be a bottleneck for this system to be implemented but there is a potential way to get the labelling done automatically. One of the easiest ways would be to use the Google Maps API to extract the information about the intersections and based on information from this method relative information such as start time and end time of intersection can be extracted in real time. Based on that all the measures can be extracted with way less computation as compared to deep learning and image-based measures. Another way to extract the information would be to use object detection algorithms to identify the type of intersection based on image and then measures can be extracted. There were a lot of measures I have used but most of them can be extracted with minimal number of signals. Mostly there were 3 major signals used in this study which were time, distance and speed. All these signals are available on CAN data and the frequency of the data is also high which makes these signals with higher amount of resolution which can increase the accuracy of the overall system. Overall vehicle centric and feasibility of implementation lead to a real time, unique and least complex solution possible to extract driving behavior measures at most common type of intersection encounters any driver can have in daily driving. This study also used physiological measures to identify the difference in physiological patterns while applying the brakes just before the intersection. There are different manufactures developing products like a smart watch capable of recording the physiological signals of any individual. With all the physiological signals used in this study can be recorded within next couple of years.

Results of the experiments conducted showed some significant difference in both individual level and group level. T-test results confirmed that there is statically significant difference between MCI and Non-MCI group of drivers. At individual level BR signal showed significant correlation with Processing Speed function. MCI drivers found not to comply with a stop sign more as compared to Non-MCI group of drivers. Overall both groups failed to comply with stop sign in all the stop and go scenarios. From this experiment it cannot be concluded that with small help from the vehicle they will comply with stop and go action required at intersection. Based on these results I found it feasible to train a machine learning model and the accuracy of the model was not per my expectations but on a smaller dataset I would say these results are promising. On a larger dataset we can expect better classification performance from the model. With a much larger dataset I would advise anyone to use a neural network for training and testing purposes.

In this study, I was able to identify significant difference in driving behavior between MCI and Non-MCI group of drivers. I was also able to relate a cognitive ability with driving behavior measure which can be used to identify the type of driver based on Processing speed function.

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