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# Nature of Distracted Driving in Various Physiological Conditions

**Yihang Chu[1], Hasanur Rahman Chowdhury[2], Abu Mitul[3], Nezam Uddin[4], Mohammad Jobayer Hossain[5], Dean M. Aslam[6]**

Electrical and Computer Engineering Department, Michigan State University, MI 48824[1-4]

CREOL, The College of Optics and Photonics, University of Central Florida, FL 32816[5]

Biomedical Engineering, UT Southwestern, Dallas, Texas (Adjunct Prof.)[6]

Roswell Park Comprehensive Cancer Center, Buffalo, New York (Adjunct Prof.)[6]

Elect & Computer Eng., Michigan State University, E. Lansing, Michigan (Prof. Emeritus)[6]

**Abstract:** Road traffic injury has appeared as a severe problem today, claiming more than 1.25 million lives each year worldwide and draining 3% of the total global GDP. According to the National Highway Transportation Safety Administration, about half a million people got injured in 2014 due to distracted driving related car clashes. In this work, we have considered the brainwave, heart rate and blood pressure level of a distracted driver. Within the various source of distraction (e,g, multitasking, severe weather condition, external sound effects) we monitored the driving behavior through EEG signal. In particular, the alpha, beta, gamma, delta and theta brainwaves have a significant connection with the emotion, stress and other psychological responses. Our EEG data analysis can provide a pathway to detect the physiological condition of distracted drivers and avoid road accidents.

**Keywords:** Electroencephalogram, brainwave, driver monitoring, driver distraction, attention level, meditation level

## I. INTRODUCTION

Road traffic accidents have become the number one cause of death in modern society for those aged 15-29 years (figure 1), as well as the ninth leading cause of death globally [1]. Within the foreseeable future, these statistics will only worsen without the application of significant countermeasures as more and more vehicles are produced each year, with a record 67 million passenger cars manufactured in 2014 alone. Among the causes of road traffic accidents, the National Highway Traffic Safety Administration (NHTSA) has ranked driver distraction at the top, playing a role in at least 25% of policereported crashes [2]. Based upon this information, one effective means to combat road accidents is the development of a driver monitoring system to evaluate driver distraction and potentially provide alerts prior to the occurrence of accidents.

As countless possible sources of driver distraction have emerged in modern society which typically act upon the driver in combination, a driving need exists for a unified definition and model of driving distraction which incorporates all aspects of dual-task interference outside the vehicle, within the vehicle, and within the driver [3]. Many classification systems have emerged, from the division of in-vehicle and out-of-vehicle distractions to the categorization of visual, auditory, biomechanical and cognitive distractions based upon their impact upon the driver [3, 4]. In this article, driver distraction shall be divided into the two major categories of internal distractions which stem from within the driver's self and external distractions which stem from outside sources. Internal distractions are not directly impacted by outside factors, and may include mental sources such as strong emotions, stress, wandering thoughts and disabilities as well as physical sources such as fatigue, illnesses and drug use. Meanwhile, external distractions vary widely in scope and can include both those within the vehicle and outside the vehicle. With the advent of the wireless communications age, the use of mobile devices, entertainment systems and GPS navigation technology in cars has become increasingly common, resulting in new sources of distraction such as texting, music/audiobook listening, GPS reading, etc. joining previous sources such as outside objects/events, passenger actions, food consumption and make-up application.

The determination of the presence of such distractions through sensors and data within drivers has been an ongoing research topic over the past decade, and multiple methods have emerged to prominence based upon a variety of data types. Through circulatory system data such as heartbeat, blood pressure and blood oxygen content which can easily be measured via electrocardiogram (ECG) wristband monitors, general fitness and stress profile data can be accumulated upon the driver to estimate their mental and physical status [5].

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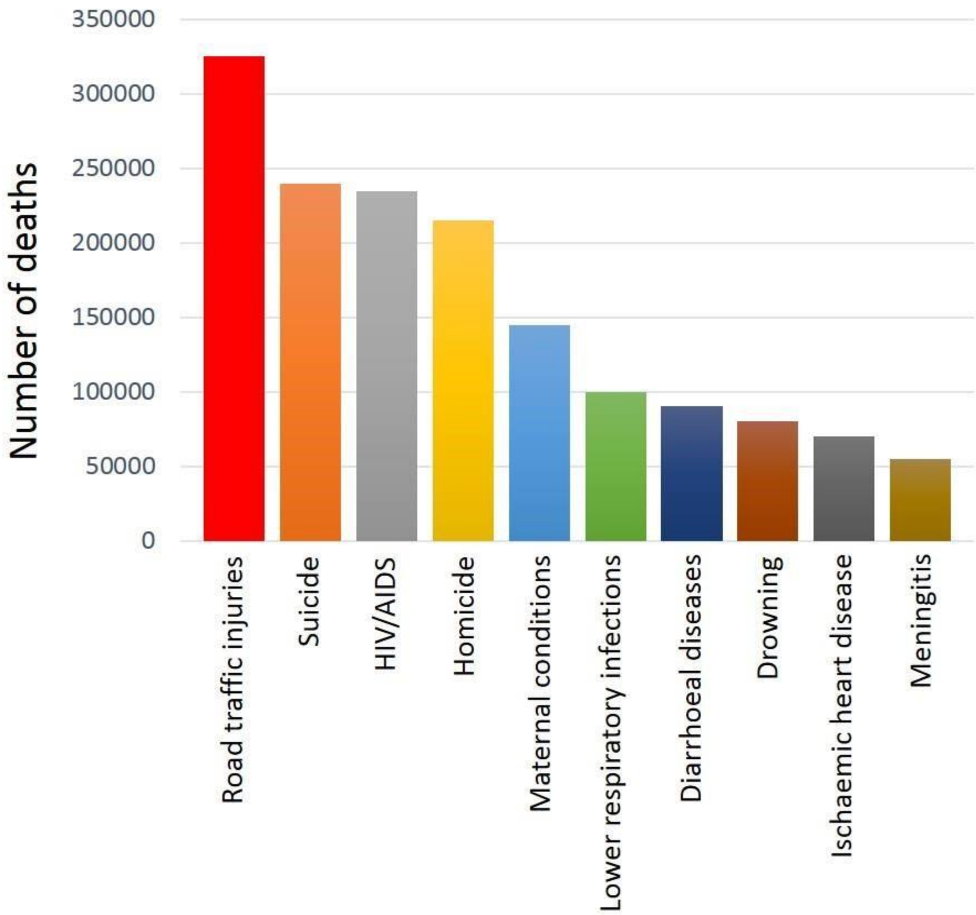


Figure 1. Top causes of death for individuals aged 15-29 years in 2012 [6]

In combination with brainwave data acquired via electroencephalogram (EEG), an estimate of the driver's emotional state and degree of distraction can be made based upon a built-up psychological model [7]. Among non-contact monitoring methods, video analysis has emerged as a powerful tool, being capable of determining the driver's mental and physical state through head gesture, eye movement and facial expression tracking [8, 9]. Through coordination of contact and noncontact driver monitoring methods to offset advantages and disadvantages, a reliable driver distraction estimation system is already close to realization.

## II. NEW AND EXCITING ASPECTS

Recently, the field of driver distraction detection for crash avoidance has received increasingly focused attention in response to the steadily increasing count of global vehicle accidents born of the expanding automobile industry. Reagan et al. investigated the crash avoidance and driver assistance technologies at the Insurance institute for highway safety, VA, USA in 2017. Researchers from this institute focused on front crash prevention, blind spot monitoring, rear-traffic cross alert and driver monitoring alert. While working with lane maintenance systems, they used camera sensors and a car speed of 35 mph. They investigated the forward collision warning and autonomous emergency braking system of multiple cars, alongside the percentage of crash avoidance systems to turn on in various manufacturers including Cadillac/ Chevrolet, Ford, Honda, Lexus, Toyota, Mazda and Volvo. Their experimental results are depicted in figure 2a [10].

Focusing more upon user input, Ahmed et al. introduced Homonoia in technology which investigates the driver`s mood using EEG signals and its implementation in future vehicle technology. Their proposed vehicle system linked the user to autonomous components, such that the driver`s brainwave would be factored in for the vehicle control system [11]. Similar research has been seen by Utama et al. in 2017 where they used the Neurosky mindwave mobile device to control a wheelchair (figure 2b). They investigated the forward, backward, right turn, left turn movements of a wheelchair commanded via brain signals with an average success rate of 80% [12]. Their proposed system suggests that it`s quite possible to develop an embedded system which might help to control the car motion via brain signals.

 

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The brain has an instinctive desire for survival, and while thrust in an accidental situation, damage mitigation may be possible if the car can be directly controlled. However, in cases where the brain`s activity may be traumatized due to excessive stress, some safety measures can be designed to trigger autonomously. For example, if the car`s embedded system can measure the trauma/stress/emotional level of the user, it could drive autonomously and maintain a safety distance in place of the user when necessary.

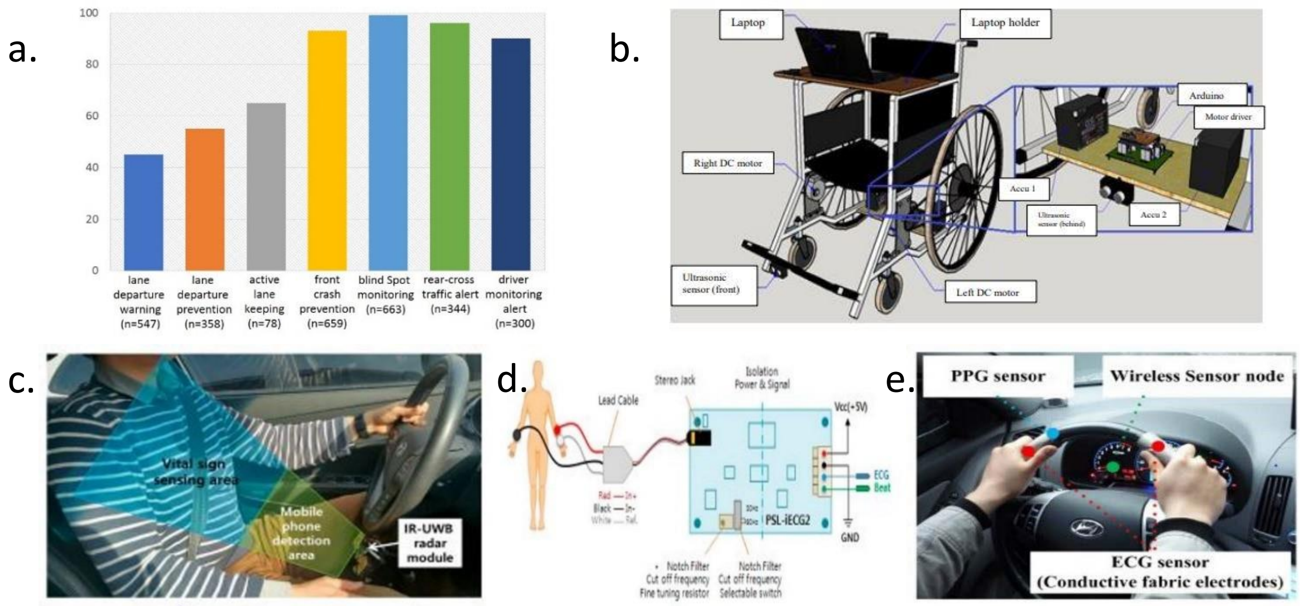


**Figure 2.** (a) Percentage in turning on the crash avoidance technologies [10]. (b) Brainwave-controlled wheelchair by Utama et al. in 2017 [12] (c-d) Measurement setup and ECG signal acquisition by Guo et al. in 2018 [13] (e) Car driver`s condition monitoring system by Shin et al. [14]

More recently in 2018, Guo et al. researched the brainwave signal in different weather conditions using Neurosky mindwave mobile with an overall system as depicted in figure 2c-d [13]. Their research results indicated a direct relationship between the fogginess of the weather as well as the ideal attention level of the driver, and presented a useful study of the effects of different driver distraction levels upon accident evasion. In similar work, Sung et al. studied vital sign monitoring and mobile phone usage detection using IR-UWB Radar for intended use in car crash prevention. They noninvasively monitored the driving behavior through impulse radio ultra-wideband (IR-UWB) radar to gather vital sign data including respiration rate and heart rate, both important measures for the driver's drowsiness condition [15]. Finally, Shin et al. successfully developed a car driver condition monitoring system using PPG and ECG sensors. Their system architecture is shown in figure 2e [14].

## III. METHODOLOGY

This work is focused on the development of a technology which might have a feedback system to alert the driver depending on their measured distraction level due to different external or internal factors. In this work, driving behavior was explored via the application of different forms of external and internal distraction to the driver. Through a series of experimental trials, data regarding the brainwaves (attention and meditation levels) of a subject driver was gathered under conditions of distraction. The driver's age is a category which must be defined first as the literature suggests that teens generally possess higher distraction levels and accident rates, which inspired the consideration of subjects of ages between 21 and 27. The age of the subject driver was between 25 to 30, which falls in one of the categories shown in figure 3, while the gender, ethnicity and hunger levels were respectively male, Bengali and medium. The data gathering procedure took place at night prior to sleep with the subject driving upon a familiar road under snowy conditions. By means of a Neurosky Mindwave headset, the subject's EEG data was recorded over five-minute intervals corresponding to distraction levels characterized by: normal driving (no distraction), talking with a passenger, listening to rock music, texting, and listening to religious talk. In following data processing, the average and standard deviation values of the attention and meditation levels over these five-minute periods were recorded and analyzed to examine the variance in effects of different distraction sources upon the driving subject.

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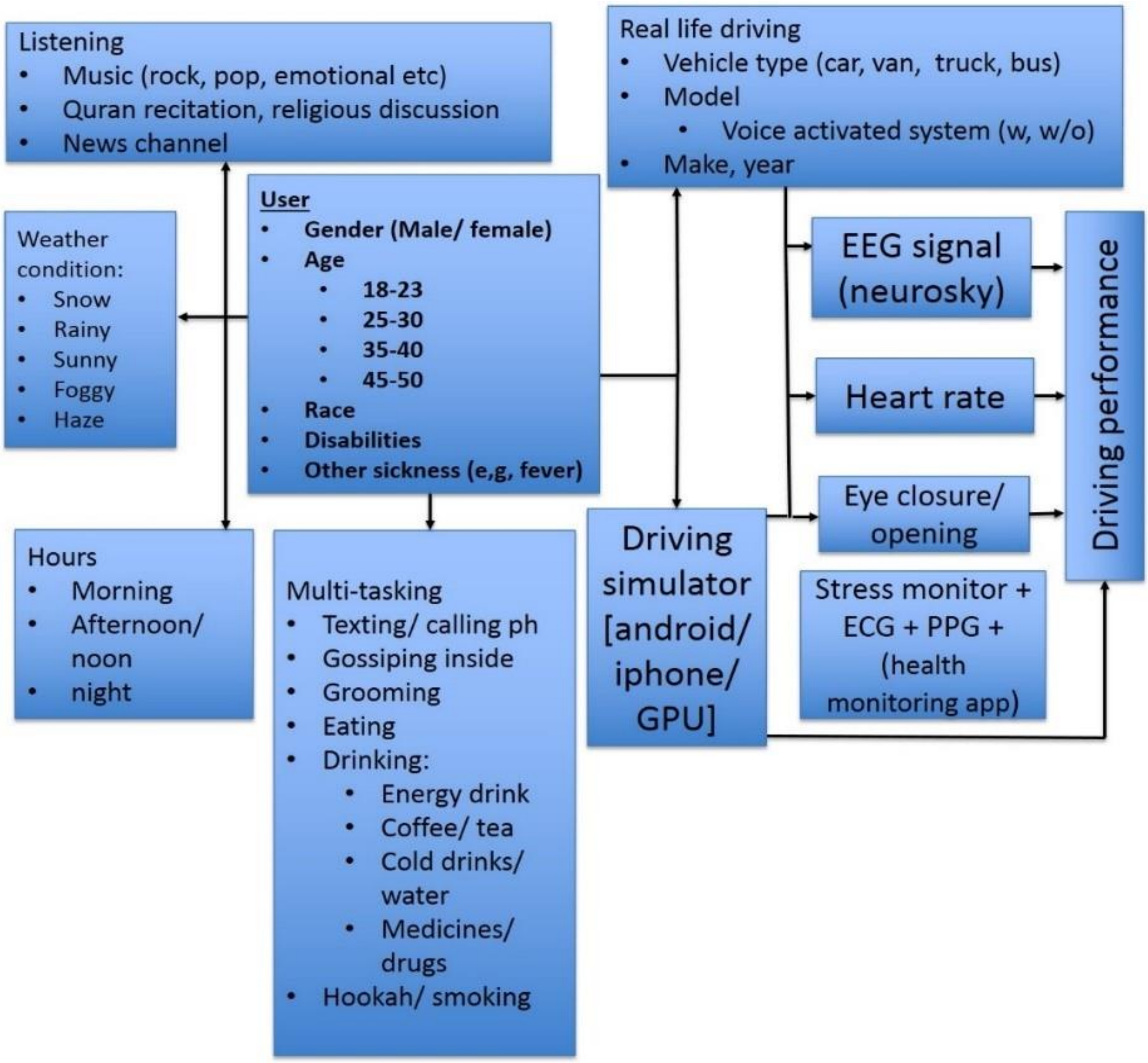


Figure 3. Proposed personality detection scheme for a car

Previously, researchers focused on ECG, EEG or PPG data for driving in different conditions, but did not deeply consider the level of distraction beyond drowsiness [16, 17]. In other work, driving simulators were used for distraction level measurement, but focused only on the beta brainwave value [18, 19].

The uniqueness of this work lies in the gathering of driver brain signal data measured via the Neurosky Mindwave headset in genuine driving conditions with clearly defined elements of distraction. Further factors which distinguish the driving conditions include the familiarity of the driver with the road, the lack of light due to night, the sleepiness of the driver, and the presence of snow as a driving hazard.

Though the framework for experimentation in additional subjects with different types of distraction alongside the measurement of circulatory system data was in place, limitations of time and funding have limited the scope of the investigation. Figure 4 shows the workflow diagram of the current project. The results are recorded and examined in Section 4.

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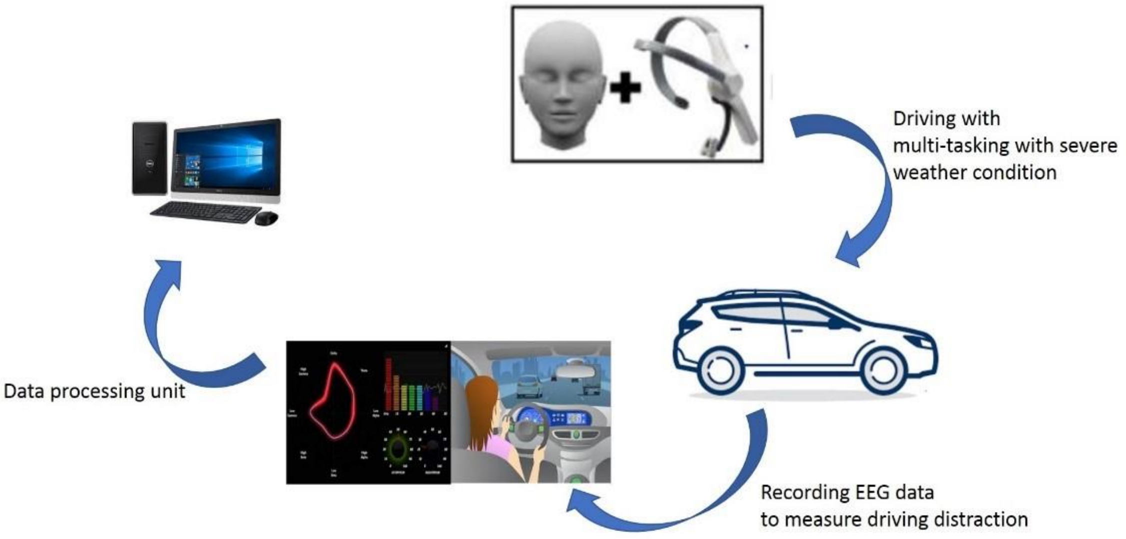


Figure 4. Workflow diagram in current project

## IV. RESULTS/ANALYSIS

An experiment was conducted to examine the attention level and meditation level of a person while driving through various sorts of distractions. In this test, a Neurosky Mindwave headset was employed which was able to safely measure and provide outputs as EEG power spectrums (alpha, beta, gamma waves, etc.) and determine attention and meditation level through the eSense algorithm. The device consists of mainly three components- (i) a headset, (ii) an ear clip, and (iii) a sensor arm, which is placed against the forehead of the subject. A healthy male adult was taken as the subject and he was led to drive through five different conditions:

1. Normal state (no distraction)
2. Driving while talking
3. Driving while listening to music
4. Driving while texting
5. Driving while listening to religious talks

Attention and meditation level were measured during the driving test and data was taken over a five minute period for each of the conditions mentioned above. Figures 5(a) and 5(b) show the attention level and meditation level vs time, respectively, while figures 5(c) and 5(d) display the average attention and meditation level values of the subject under various sources of distraction. The mean and standard deviation values of the attention and meditation levels are summarized in Table 1:

Table 4. Mean and Standard Deviation (SD) values of attention and meditation levels for different kinds of distractions

| Parameters | Value Type | Driving (Normal) | Driving while Talking | Driving while Listening to Music | Driving while Texting | Driving while Listening to Religious Talk |
|---|---|---|---|---|---|---|
| Attention Level | Mean | 48.6 | 47.4 | 62 | 57 | 53.2 |
| | SD | 3.847 | 6.348 | 3.162 | 3.240 | 5.805 |
| Meditation Level | Mean | 56.6 | 51.6 | 54.666 | 56.6 | 59.8 |
| | SD | 5.029 | 4.50 | 4.366 | 3.507 | 3.898 |

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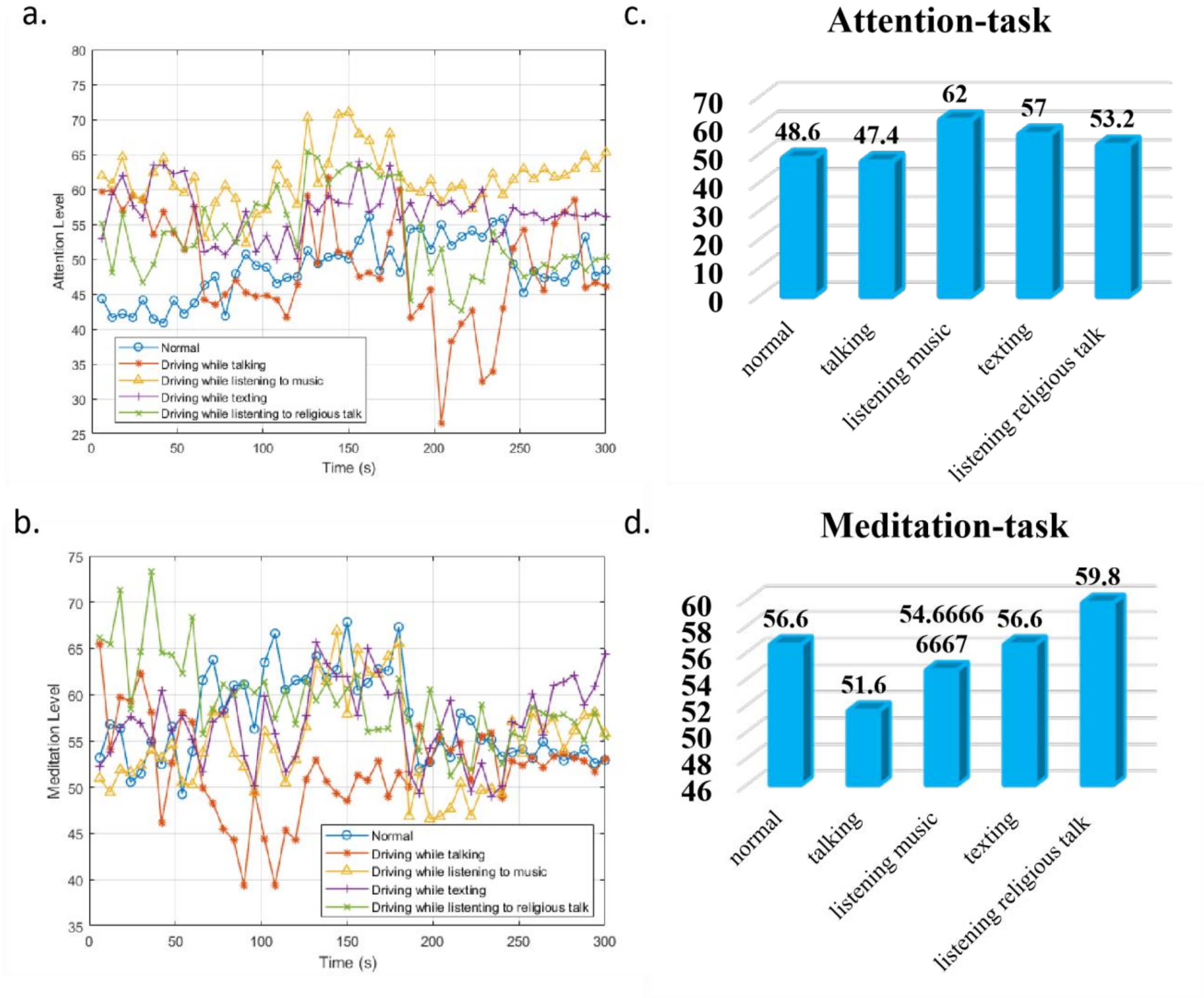


Figure 5. (a) Attention level and (b) Meditation level vs time for different kinds of distractions. (c-d) Bar charts for attention and meditation level averages for comparison.

From the graph it is seen that attention level increases for various kinds of distraction. This is due to the fact that the brain needs to perform multitasking while driving with other tasks (like talking, texting, etc.), thus requiring greater focus. The highest attention values were found for driving while listening to music (average attention level is 62 for music, in comparison to a value of 48.6 for normal driving). Based upon this data, it can be concluded that music functions as a vital element of distraction while driving. Meanwhile, the gathered driver data with the distraction element of talking displayed the greatest variance in value, which can be considered evidence of the shifting mood of the driver in response to changes in conversation topic.

From the meditation graph, the data does not show many conclusive results, suggesting that meditation level is not significantly affected by the examined distractions. However, the highest meditation values were found while driving and listening to religious talk. Since religious talk and recitation are known to help humans feel calm, the meditation level increase in this case (59.8 in comparison to a value range of 54-56 at normal state) can be rationalized. Similar to the attention level data, the meditation level also displayed the greatest range of variance under the distraction element of talking, which can again be attributed to the shifting mood of the driver. Though the data is not enough for statistical analysis, the effects of different kinds of distraction can be clearly observed, especially with attention level. This experiment indeed gives an idea of the mental state of the driver for various distractions, which agrees well with practical experiences in daily life.

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## V. FUTURE RESEARCH

A total of 515,000 people were injured in 2014 due to car crashes originating from distracted driving based on data from the National Highway Transportation Safety Administration. These statistics alongside similar past records led US Secretary of Transportation Ray La Hood to proclaim distracted driving as a "menace to society" [20]. In this work, the brainwave, heart rate, and blood pressure level of a distracted driver has been investigated, though further analysis was impossible due to the unavailability of resources. In particular, the alpha, beta, gamma, delta and theta brainwaves have significant connection with the emotion, stress and other psychological responses of humans. The majority of brainwavebased research has mainly ignored such details and focused upon the detection of individual factors such as stress, distraction and fatigue for evaluation rather than building a concrete model of the human emotions. While this work focused upon discovering the driver's mental response to distraction sources such as rock music, qur`an recitation, texting and talking begins to touch upon the domain of monitoring the changes in the driver's general moods and emotions, this merely scratches the surface. The sources of distraction remain lacking, and very little research has been performed regarding the change in driver data when facing sources of distraction including eating, drinking or sudden nearby events such as accidents. Recent research shows that the voice-activated systems of some vehicles are also a significant source of distraction. The American Automobile Association (AAA) for traffic safety investigated the voice-activated systems of the Chevy Equinox, Buick lacrosse, Toyota 4Runner, Ford Taurus, Chevy Malibu, VW Passat, Nissan Altima, Chrysler 200c, Hyundai Sonata and Mazda 6, scoring the distraction level from 1 to 4. Their research shows the highest level of distraction was found in the Mazda 6 [21]. The presented research can be extended to find brainwave signal variation in such voice-activated cars and find an optimized voice activation system solution for comfortable driving with minimized distraction. The authors express interest in extracting the EEG signal using various mathematical models such as time frequency distributions (TFD), fast fourier transform (FFT), eigenvector methods (EM), wavelet transform (WT) and auto regressive methods (ARM) for further analysis in hopes of categorizing the differences in driver response based upon race, gender, diet variety and stress level [22]. This approach represents an opportunity to document the differences in the ability to tolerate multitasking and general attention/meditation levels which appear when comparing humans of different races, genders and habits. In the future, once the associated research regarding brainwave mapping and analysis via EEG reaches maturity, driver monitoring systems may one day be capable of building a complete psychological profile of each driver based upon the five primary brainwaves, and thus be able to react to and categorize the causes of all minor changes to brainwave fluctuation beyond the commonly monitored parameters.

A further extension of interest in this research exists in the detection of the influence of chemicals upon the driver's physiological and physical state by driver distraction monitoring systems. Most prominently, due to the intention of legalization of marijuana in multiple states, a necessity exists to proceed with further research in the direct influence "medical marijuana" upon drivers. Currently, the research field of medical marijuana has exploded with activity, and an extremely interesting direction may be the monitoring of the distraction level in drivers utilizing medical marijuana through brainwaves (attention or meditation levels) [23-25]. Greene et al. have proceeded in this direction and described the acceptable regions of medical marijuana use while driving in 2018 [26]. This work can thus be extended to the monitoring of marijuana-using drivers in multitasking and hazardous weather conditions to provide an overall guideline for future marijuana users.

Meanwhile, previous research indicates that intoxication from alcohol increases the risk of car crash to a greater degree than intoxication from marijuana [26]. A driver can be arrested if their blood alcohol content (BAC) is 0.08%, and the monitoring of this parameter is of the upmost importance. The driver surveillance system, if capable of reliably detection the condition of inebriation, may be used to directly report data to law enforcement or signal alarms such as the emergency lights on the outside as a warning to nearby cars. For drugs legal to use in combination with driving such as smoking and hookah, interest exists in recording the associated brainwave signals for distraction level analysis under an array of weather and multitasking conditions. As both drugs and multitasking (texting, eating, talking, etc.) serve as sources of distraction, a study of the variations in brainwaves generated once both are combined in the driver is called for. Based upon the results of such an analysis, the degree of distraction which may be tolerated by drivers under the influence of various drugs of varying dosages may be estimated for driving safety.

Lastly, a final topic of interest is that of the brain-computer interface (BCI), which could be the key to formulating a system which integrates the driver's intentions with the car itself. With access to the driver's psychological profile and circulatory system data alongside external monitoring technologies, such a system could directly take measures to assist the driver in practice, or in cases of extreme distraction or unconsciousness, switch to an autonomous driving mode to bring the car to a safe stop. With the accumulation of driver data, these autonomous actions may be expanded as the car's feedback system self-optimizes to reduce stress and react to different emotions for user comfort once the technology

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reaches its peak, forming the next generation of technology beyond the modern smart car. In an example of the limits to which such technology could reach, Utama et al. developed an EEG-based system which enabled the researchers to move a wheelchair based on their brain signals [12]. As future smart cars are likely to be designed with small and autonomous structures, the integration of such technology could represent an unprecedented balance between autonomous driving and driver direction, allowing one to make up for any errors in the other.

## VI. CONCLUSIONS

As of the time of writing, the interest in the topic of driver distraction detection for accident avoidance is rapidly rising due to the global effort to reduce vehicle-related deaths in response to the expanding automobile market. In this article, a thorough introduction to the various means through which driver distraction detection can be achieved was presented alongside the methods through which EEG data in particular is processed. Among contact detection methods, ECG in particular is likely to see the greatest use due to the ease with which measurements can be carried out, while EEG data collection systems may see future integration in driver helmets in advanced driver monitoring systems. Meanwhile, noncontact methods such as video data analysis and motion sensors have received focused interest due to the lack of necessity for driver cooperation and the ease with which they may be integrated in existing systems. Through EEG data gathering with a 25-30 age subject driver in snowy night conditions, this work has examined the effect of various distractions including talking with a passenger, listening to rock music, texting, and listening to religious talk upon the attention and meditation level data in comparison to regular driving data. Based upon the observations, rock music is associated with the highest attention level values in the subject, while religious talk was linked to the greatest meditation level values. Of particular note is the distraction of talking with a passenger, which generated the greatest fluctuations in attention and meditation level corresponding to the driver's changing moods. Though the development of driver distraction detection technology has initially accelerated in recent years in response to the recent surge in accident reduction measures, the wide range of applications and large range of potential impact this research domain possesses will ensure that it remains a blazing focus of researchers for decades to come.

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