Effect of Conversation during Driving: Towards Increased Mental Load and Virtual Lateral Vehicular Variation

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Abstract

Using virtual reality on a driving simulator is a very important technique to detect driver behavior. It is a very common method to study driver behavior because it provides a safe research environment. This provides an opportunity to design a virtual world that can closely replicate the real world to help researchers collect data from subjects to understand drivers' behavior in certain situations. Driving is associated with various visual and auditory signals that are controlled by cognitive factors. Fatigue and distractions are common experiences associated with driving and directly related to the mental workload of a driver. In this paper, the lateral variation characteristics (speed variability and maintenance of lane positioning) are measured on a virtual 10-mile stretch of Florida highway, Interstate 10 (Exits 199 to 209 A/B), to understand drivers' behavior during lane changes and secondary tasks. This is a pilot study performed to help identify the root cause of the high number of traffic accidents on highways. Data were collected from 18 healthy subjects. Each subject participated in two sessions, one involving individual driving and the other with distractive driving with co-passengers. Results imply that speed variability in the second session is much higher than during the first session in the case of younger drivers. Also, lane maintenance was poor while driving with co-passengers. Mental workload was also estimated for each subject, using NASA TLX. Mental workload was also higher for younger drivers than elderly drivers for the same task. People with a higher mental load index were more distracted while driving. This paper also includes a general driving model that shows the driving trends of young and elderly drivers. The model quantifies the fact that younger drivers have a tendency to drive faster, which may add risk in highway driving in certain situations.

Introduction

Driving is an unavoidable task in most of the parts of the United States. US highways are shared by drivers of different age groups, ranging from 16 to 75 years of age (Wang & Knipling, 2004). Florida, especially, has many elderly drivers. Records from National Highway Traffic Safety Administration (NHTSA) indicate that 37,486 people were killed in 34,436 motor vehicle crashes in 2017, an average of 102 people each day (Bengler,

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Dietmayer, Farber, Maurer, Stiller, Winner, 2014). Figure 1 shows the top 10 states with the highest number of accidents; clearly, Florida has more accidents than any other state. Since the researchers reside in Florida and have access to information that can explore these statistics (Ohn-Bar, Tawari, Martin, & Trivedi, 2015), it is reasonable that this work focus on statistics that impact Florida drivers.

US States With the Most Car Accidents

Rank	State	Number of Crashes
1	Florida	1011
2	Tennessee	437
3	New Mexico	344
4	Alabama	336
5	Louisiana	271
6	Texas	268
7	Arizona	249
8	Washington	245
9	South Carolina	244
10	North Carolina	201

***Figure 1*. State wide car crash statistics [5].**

Florida is a large state; it is still smaller than California, so population is not the reason for excess accidents. Road design, driver age, and the rate at which people drive can be contributing factors to high crash percentages. Among total crashes, according to NHTSA, 40% are due to improper lane maintenance, and almost 95% of those are fatal. Figure 2 shows factors for accidents (Shantinath, Ramdas, Hanumant, & Sudhakar, 2015). Accidents occur during lane changes, due either to speeding or slow driving. Speed variation can be due to driver distraction, and this aspect needs further exploration to achieve a solution for safer lane changes. Further review of the literature reveals a very high number of accidents at the I-10 region in Tallahassee. The ramps of the exit are 360º circular for this region. A rapid decrease in speed from 75 mph to 36 mph in a circular path can be difficult for many drivers, especially the elderly. It might be a primary cause of crashes (Mogelmose, Trivedi, & Moeslund, 2012).

From Figure 2 , it is clearly evident that most of the accidents in Florida are due to improper lane maintenance. Hence, this factor needs some serious attention in order to check the crash rate on state highways (Wilson-Jones, Tribe, & Appleyard, 1998).

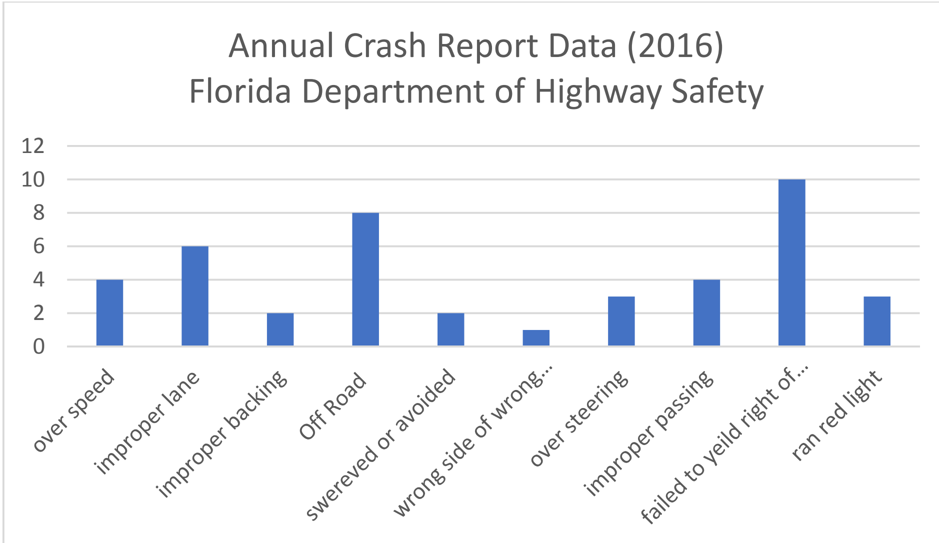


***Figure 2*. Statistics showing factors responsible for road accidents.**

It is also important to know which age group is facing the highest number of crashes in order to study the behavioral differences in drivers' age groups. Male and female drivers usually have different response time/reaction time to stimuli. Florida Department of Highway Safety and Motor Vehicles also published a study that states the age groups that are highly exposed to accidents on highways (Trivedi, Gandhi, & McCall, 2007). As Figure 3 indicates, young and elderly drivers have more accidents than average aged groups.

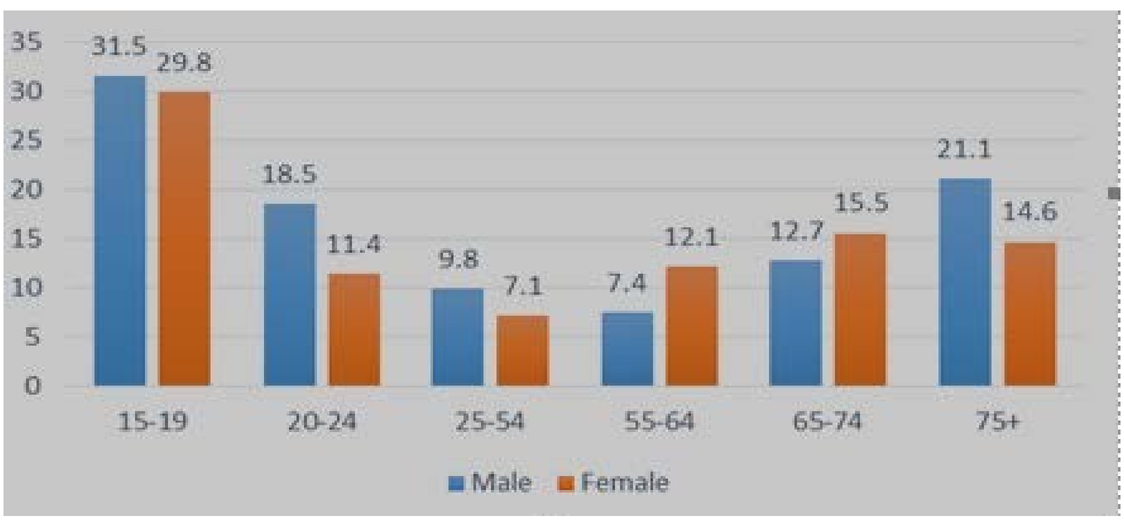


***Figure 3*. Florida highway accident statistics.**

The age group between 15 and 19 usually has good eyesight whereas 75+ may have deteriorating eyesight, but both are prone to accidents. This definitely implies that eyesight is not the reason for accidents, and distraction or reaction time might be a possible reason for crash in these age groups (Cheng & Trivedi, 2010).

Driving is a task that demands mental attention. A few seconds of distraction might cause a fatal crash. Using a cell phone has been the main focus of recent research as the most distracting task in fatalities (Peng, 2002), but a 2017 NHSTA accident report notes other factors that seem to cause more accidents (Hess & Modjtahedzadeh, 1990). Figure 4 shows the various factors that can distract a driver on the road, and the most dangerous distractive task is interacting with co-passengers (Yakub & Mori, 2015). Talking to other passengers about topics that elicit the driver's emotion to a great extent (like anger or depression) can distract the driver and, as a result, cause fatal highway accidents (Pentland & Liu, 1999). These kinds of emotions might add to the mental load of the driver (Hart & Staveland, 1988).

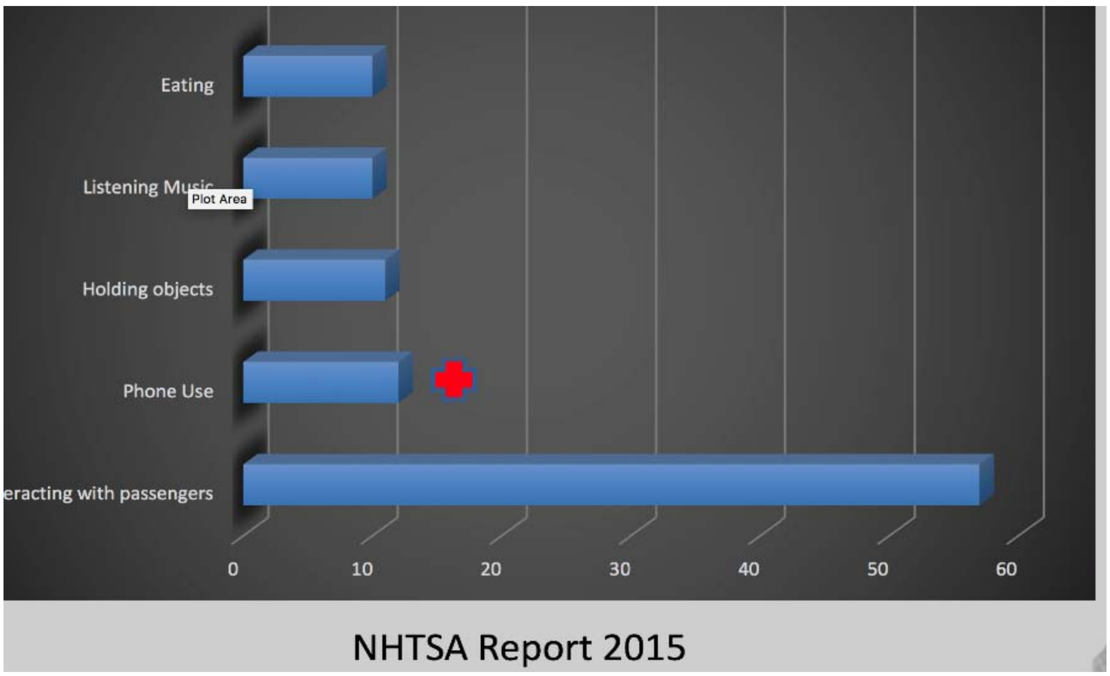


Figure 4. **Different secondary tasks causing driver distraction.**
(Marilyn: NHSTA don't need permission, but they do need acknowledgment as to source)

To investigate and validate this problem, this study has been conducted with two age groups of drivers (20-35 years) and (55-60 years), driving in two scenarios: alone in the car and with two to three co-passengers discussing emotional topics. Driving data can be obtained in two forms, real-time driving or data from a driving simulator. Most researchers prefer to collect the initial data on a simulator as it provides an inherently safe atmosphere for research. It is easier to control experimental conditions on a simulator (Wilson-Jones, Tribe, & Appleyard, 1998). They are usually linked to a computer for online data processing and storage of data for further analysis.

On the other hand, the driving simulator environment is virtual, which might affect driving behavior (Hart, 2009). Hence, there is an issue of reliability when using a simulator. After collecting data from a simulator, researchers typically validate the result with real-time data to modify the driving scenario for accuracy and precision (Cao, Chintamani, Pandya, & Ellis, 2009).

In this study, we used a driving simulator to collect data. The study involves lane maintenance and speed variance in these two scenarios, monitoring from the simulator with some statistical analysis to analyze the general driving behavior on a highway. Also, the mental load of the drivers is analyzed with NASA-TLX after the first session to understand the mental work demand on a driving simulator (Salvucci & Liu, 2012). Each participant also completed a survey questionnaire for data collection, to store driving history. All drivers were trained on the simulator before the actual data collection, and they signed a waiver before their participation in this research.

System Design

System design in this experiment involved scenario design on the driving simulator. The scenario is designed based on local intersections in Tallahassee, Florida, along I-10 (Exit 209A/B) that are known to have a higher than average rate of roadway incidents (Salvucci, 2004). The environment is designed to replicate the I-10 209A/B exit as closely as possible. The scripting language for controlling the traffic in the virtual world is TCL, a scripting language used in Hyperdrive (Kuge, Yamamura, Shimoyama, & Liu, 2009).

The scenario starts from merging into the highway from an exit with flowing traffic and then driving on a three-lane highway with various curves. There are two exits designed with ramps mimicking 209A/B. This exit is a one-lane, circular road. The simulated 3D design is shown in Figure 4.

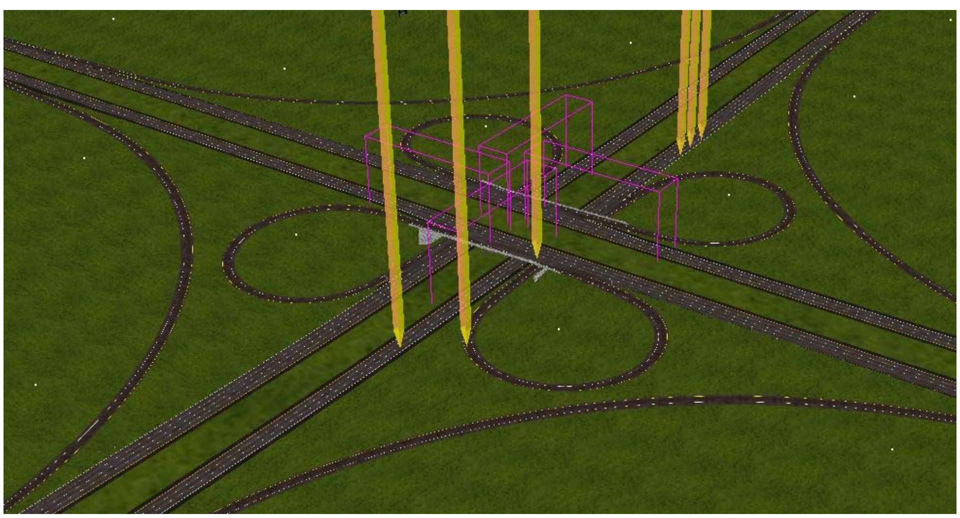
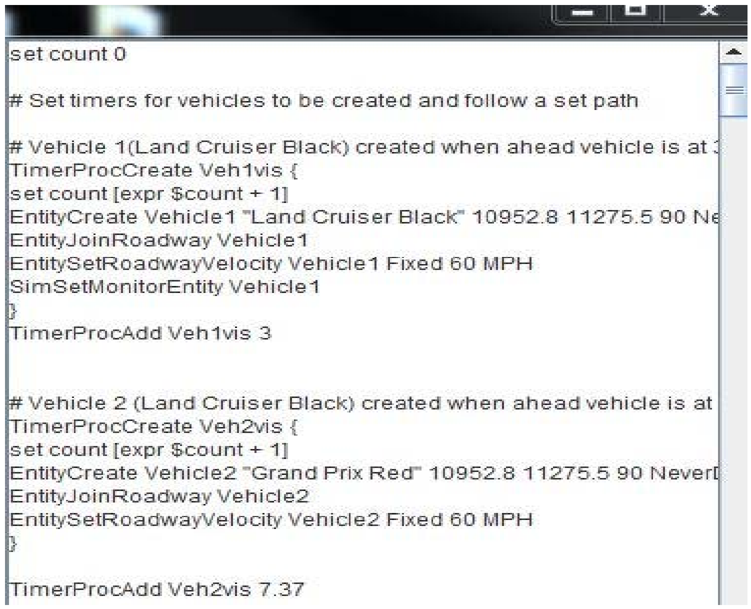


Figure 4. 3D Simulated design of Exits 2019A/B.

The scenario is programmed to include location triggers (yellow lines in Figure 4). Hyperdrive supports TCL scripting, which is a high-level machine language, and hence the simulated cars are introduced in the scenario by writing code in TCL (Salvucci, 2006). An example of this scripting is shown in Figure 5. Thirty-two vehicles of different makes and models are used as well as commercial vehicles like buses and 18-wheeler trucks. When the participant's car approaches the location trigger to merge onto the highway, all these 32 cars starts generating one after another to form the highway traffic.



```
set count 0

# Set timers for vehicles to be created and follow a set path

# Vehicle 1(Land Cruiser Black) created when ahead vehicle is at :
TimerProcCreate Veh1vis {
set count [expr $count + 1]
EntityCreate Vehicle1 "Land Cruiser Black" 10952.8 11275.5 90 Ne
EntityJoinRoadway Vehicle1
EntitySetRoadwayVelocity Vehicle1 Fixed 60 MPH
SimSetMonitorEntity Vehicle1
}
TimerProcAdd Veh1vis 3


# Vehicle 2 (Land Cruiser Black) created when ahead vehicle is at
TimerProcCreate Veh2vis {
set count [expr $count + 1]
EntityCreate Vehicle2 "Grand Prix Red" 10952.8 11275.5 90 Never[
EntityJoinRoadway Vehicle2
EntitySetRoadwayVelocity Vehicle2 Fixed 60 MPH
}

TimerProcAdd Veh2vis 7.37
```

Figure 5. TCL scripting for simulated car.

Eighteen subjects participated in this study, and everyone completed the entire task successfully. All subjects who participated in this study had been driving for at least two years in the United States. None of the participants had a history of any major or minor accidents within the last two years. Before the experiment started, participants completed a questionnaire to assess their driving history and typical driving behavior. The survey had 23 questions ranging from specific demographics to decision-making questions such as (Salvucci, Boer, & Liu, 2001):

- How do you usually merge from a ramp onto the freeway?
- Do you usually face any difficulty/challenge when you are about to merge onto a freeway?
- Do you usually maintain the same lane after you merge onto the freeway, or do you change lanes?
- Do you usually face any challenge/difficulty when you change lanes on a highway?
- Do you prefer getting messages by mobile or through a signal at the merge or lane change to have a safer merge/change without any delay?

After this survey, each subject received a set of instructions about how to drive on the simulator. The first session was recorded for all 18 participants, one after the other, followed by the second scenario recording one by one. The total time to record the whole experiment for all five subjects with two sessions was 2 hours and 30 minutes.

Primary Task Driving Session

This scenario lasted for about 5-6 minutes for each subject. The participant was told to merge into the highway with a maximum ramp speed of 35mph and maximum highway speed of 60mph. They were instructed to change lanes whenever possible and safe. After merging onto the highway, they were told to take the first exit. After taking this exit, the facilitator signaled them to park the car in the emergency lane, which concluded the session.

Secondary Task Driving Session

The second scenario also lasted for 5-6 minutes. In this scenario, the instructions were all the same as for the first scenario, except this time the participants were told to take the second exit instead of first after merging onto the highway. The speed limit and lane changing instructions were the same. In addition, three passengers were introduced in the car along with the driver. The driver and co-passengers were instructed to converse about random topics that involved discussion and some mild debate. So conversation with co-passengers was the secondary task in this scenario. Immediately after this session, the participant was instructed to take an online questionnaire about the driving task on the NASA TLX website in order to evaluate their cognitive mental load after driving.

Results

The results show a comparison of driving behavior between two age groups. Data are taken directly from simulator and converted into Microsoft Excel for analysis. As the driving speed of each subject is different, they finished the whole task at different times. So the first 280 seconds from each recording is taken for uniform analysis. In this study, we considered the velocity (mph). We also noted the maximum and minimum speed of every participant in both the sessions. Since variance is a more robust measure of performance, we determined the speed variability for each subject as shown in Figure 6. Additionally, according to some researchers, speed variability is responsible for more accidents on roadways than vehicle velocity.

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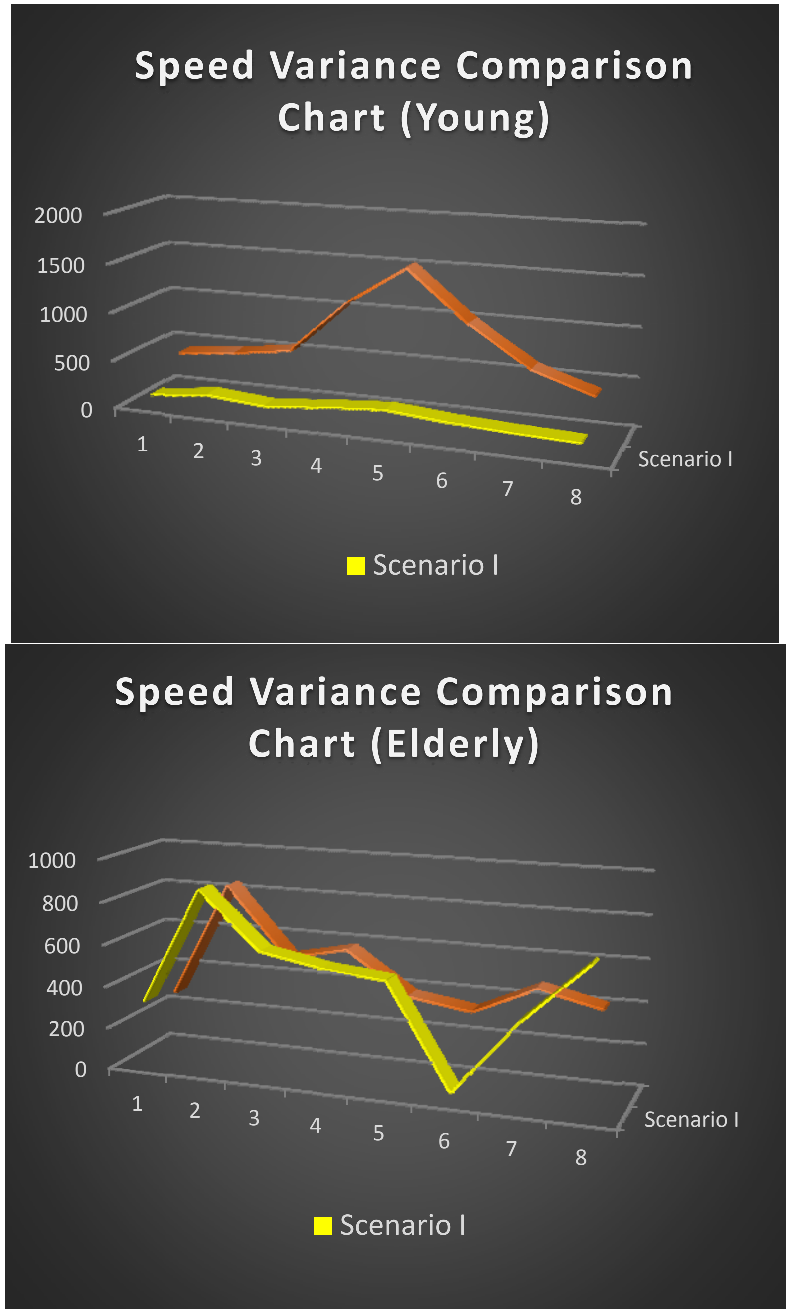

Figure 6. Speed variance comparison chart.

Result implies that the second scenario has a much higher speed variance than the first for younger adults, but for the elderly group, speed variance in these two scenarios relatively uniform.

This suggests that younger drivers were not attentive to their speed during the secondary task of conversation with co-passengers. Additionally, it is assumed that the drivers may have been distracted from the emotional response of the conversation (anger, frustration, and excitement). Also, elderly subjects have less variability in speed probably due to emotional stability during the secondary task, since they avoided talking much while driving. This can be a reason for less distraction for this age group.

Whereas younger drivers have a tendency to multitask, they were more actively participating in discussions with co-passengers while driving. From the driver simulator data, we also estimated the lane positioning of the driver continuously for 280 seconds in each trial, and we could calculate the number of times a driver touched the shoulder of the road while driving. Figure 7 compares the number of times drivers in both age groups went off-road or touched the shoulder in both scenarios.

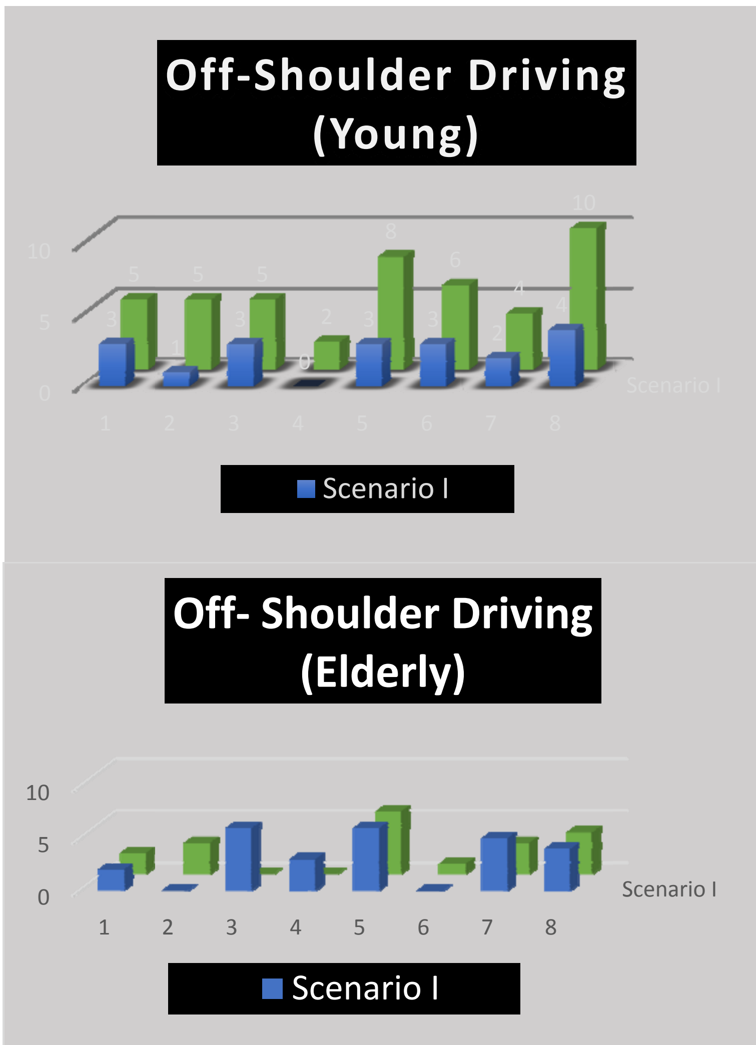

Figure 7. Off-shoulder driving comparison chart.

These data show that the young participants went off the road more times during the second scenario, supporting the argument of distraction while conversing for this age group. Due to high speed variability, younger drivers went towards of the shoulder of the road more often.

This proves that a secondary task while driving hindered proper lane maintenance. Subject 2 of the young driver profile went off road only once when he drove alone, but he went off 5 times when he drove with co-passengers. Similarly, Subject 5 of the young driver group went off 3 times during the first session and 8 times for the second. This shows a big variability of driving during multitasking. For Subject 4 of this group, the data are interesting. There is no off-road driving in the first scenario but two times in the second. There can be several reasons for this result. It is assumed that it might be driver fatigue, as the data were recorded on the same day for both scenarios. But the more logical reason might be multitasking. In the second scenario, the driver was actively talking to co-passengers for the whole session, which might have caused increased distraction. Hence, lane positioning was not well maintained while performing other tasks along with driving.

If we look at the elderly driver result, their off-road driving in the second scenario is not too high compared to the first scenario's speed variability. Elderly drivers were less distracted by multitasking and could maintain lanes more accurately than the younger group.

To gain deeper insight about causes that influence a driver's mental and emotional state, the NASA TLX results are compared with the simulation data. TLX is online software developed by NASA that is used for subjective analysis of the workload and mental load of a person. It has an online set of questions related to the performed task, and it calculates the mental load, physical load, effort, and frustration levels based on the individual's responses. Mental load in NASA TLX measures how perceptual the activity was and whether the activity was hard or easy. As driving in a simulator is more of a mental task, we have considered the cognitive mental load and the frustration level of each driver after the first scenario to evaluate total mood disturbance. Each subscale in NASA TLX ranges from 1 to 20. It evaluates cognitive factors by 15 pairwise combinations depending on the participants' response in the score sheet. The result is evaluated based on how much a cognitive factor contributes to affect other factors. Table 1 shows NASA TLX results for each of the subjects in the young profile, and Table 2 is the NASA TLX score for the elderly drivers.

Table 1. NASA TLX for young driver profile (20-30 years old).

Subject	Mental Load	Frustration	Total Cognitive Disturbance
1	81	66	147
2	82	16	108
3	91	79	170
4	81	41	122
5	64	38	102
6	18	28	46
7	58	18	76
8	72	50	122
9	27	6	33
Average			**102.88**

Table 2. NASA TLX for elderly driver profile (55-65 years old).

Subject	Mental Load	Frustration	Total Cognitive Disturbance
1	69	64	133
2	39	54	93
3	44	26	70
4	25	15	40
5	51	60	111
6	59	45	104
7	61	50	111
8	55	13	68
9	62	9	71
Average			**68.77**

The result from the NASA TLX data aligns well with our speed variance and off-road driving results. The metal load and the frustration level of each subject is considered to calculate the total cognitive disturbance for each subject. The average cognitive disturbance for the younger subject is 102.88 from Table 1, and the average cognitive disturbance for elderly subjects is 68.77. This clearly states that the elderly subjects have a stable emotional balance, and hence they are not much distracted with secondary tasks such as conversation. But the cognitive disturbance for young drivers is much higher compared to the elderly drivers in the second scenario. This is extremely dangerous, as it causes distraction while driving.

Conclusion

This paper has explained an experiment that examined behavior of lateral variation of vehicles using speed variance and off-road frequency and validation by cognitive workload measurements. This method of analysis helps in a basic understanding of driver behavior and emotional disturbances while performing a secondary task. Calculating the variance of speed and off-road driving in both individual and multi-passenger scenarios allows for more research in this field. Future studies can be conducted on the effect of emotional disturbance on drivers while talking to co-passengers or on a mobile phone. Identifying this aspect might help reduce highway accidents.

Also, this study has been conducted on younger and elderly drivers. Although it is known that motor skills and reflex actions of every person degrade with age, with conversation as type of secondary task the result is reverse, indicating more stable emotional control with age. So for younger drivers, emotional disturbance while driving might result in fatal accidents. This study validates the argument with an objective analysis of mental and cognitive disturbance to formulate an algorithm of the maximum distraction of an individual, beyond which might result in fatal accidents.

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